Innovation systems, saving, trust, and economic development in Africa

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Publication date:
2014

Document Version
Publisher's PDF, also known as Version of record

Innovation Systems, Saving, Trust, and Economic Development in Africa

Proefschrift

ter verkrijging van de graad van doctor aan Tilburg University op gezag van de rector magnificus, prof. dr. Ph. Eijlander, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de Ruth First zaal van de Universiteit op dinsdag 9 september 2014 om 14.15 uur door

HAKI PAMUK

geboren op 27 februari 1983 te Izmir, Turkije.

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Funding: The research in this thesis was financially supported by the Netherlands Organization for Scientific Research (NWO) grant number 453-10-001.

To my family...

Acknowledgements

This thesis includes my research as a Ph.D. student at Tilburg University. While writing this thesis, many people supported, helped and shared their knowledge with me. I would like to thank some of them explicitly here.

First of all, I would like to thank Erwin Bulte and Daan van Soest for their supervision throughout the writing of the thesis. When I expressed my interest in doing research on development economics to Erwin in the 2nd year of my Research Master studies, he entrusted me by giving the opportunity of evaluating the impact of a large scale development project. Thanks to him, I do research and specialize in the field which I have always wanted to work on. Besides completing this thesis might not have been possible without Daan and Erwin's help at every stage whenever I needed guidance and advice. I learnt a lot from working on our joint papers together with them and enjoyed each one of our meetings. They never stopped encouraging and supporting me, and were always patient correcting my (especially writing) mistakes.

There are also others from academia that had important contributions making this thesis possible. For instance, in the last year of my studies, I had a great opportunity to work with Thorsten Beck and Buras Uras on one of the Chapters of this thesis. Being co-authors with them was a rewarding experience, and I hope to have the chance to work with them again. Also, I am really grateful for the help and support of Fedes van Rijn for introducing me SSA-CP program and dataset - which is the basis of four Chapters in this thesis -, sharing her knowledge, and answering my endless questions. It has been (and will be) always fun working with her. I would also like to thank the external members of my PhD committee, Patricio Dalton, Michael Grimm, Menno Pradhan, and Arthur van Soest, for their time, interest and excellent feedback on my thesis. Being the teaching assistant of

Henk van Gemert and Benedikt Goderis was a significant opportunity for me, and I benefited a lot from our discussions about my research during this process.

Moving from Turkey to the Netherlands for Research Master and Ph.D. studies has been a wonderful experience, and I owe it mostly to my friends. I would like to thank my old house mates from so called “Number 9”: Aysegul Atakan, Gizem Hökelekli, and Hale Koç. Living together with these three girls was unique and experience, and thanks to sharing the house with you I have gained life time friends. And thank you, my dear friends Erdal Aydın, Enis Gümüş, Korhan Nazlıben, Ali Palalı, and Serhan Sadıkoğlu. Each of you endured my never ending complaints about Ph.D. student life and living at a foreign country. To forget those complaints we drank lots of beer and partied a lot. I have to admit that if aforementioned friends were not next to me, the thesis writing process and Ph.D. student life would be really boring.

Most importantly, I would like to thank my family for their love and support during my academic studies (*Canım ailem öğrencilik hayatımın başından bugüne kadar ki tüm destekleriniz için çok teşekkür ederim; sizler olmasanız ayakta kalamazdım*). Finally, I would like to thank my girlfriend, Ioanna for being always next to me and sharing both my stress and joy while I was writing this thesis. I could not have stood without my family’s and Ioanna’s support during these studies.

Contents

Chapter 1

Introduction

1.1 Background

Sub-Saharan Africa has the highest poverty rate and lowest human development indicators in the world. Around 45 percent of the population in the region live on less than 1.25$ per day, and this makes up 30 percent of the world's poor. Life expectancy at birth is around 54 years while it is 70 years in North America, and on average 1 in 8 children under the age of five die on a yearly basis (World Bank, 2013). These unfavourable statistics briefly illustrate why poverty reduction is an important goal for local and international policy makers.

The strategy to reach that goal should be to analyse wide ranging economic and political problems of different African[1] communities. To begin with, the role of various factors in economic development and how they interact with each other should be explored. As Rodrik and Rosenzweig (2010) stress development policy is instinctively related to different economic disciplines:

> "The policies that impact development are wide-ranging, all the way from broad macroeconomic policies such as monetary and exchange-rate policies to interventions in microfinance… Poverty reduction, economic growth, and development most broadly are the outcomes of a complex set of interactions across the entire range of economic policies and institutions. From this perspective, "development policies" must have a very broad meaning indeed." (pp. xv-xxvii)

[1] I refer to Sub-Saharan Africa when Africa term is used.

Furthermore it should be checked how broad development policies proposed for the whole region apply to separate countries and communities as neither the problems concerning economic development nor the structure of the economies are the same across Africa. For instance

- per capita income is lowest in Niger (180 international $) and highest in Equatorial Guinea (13720$);
- share of agriculture accounts 2.5 percent of Gross Domestic Product (GDP) for Botswana, it accounts 48 percent for Ethiopian economy;
- around 81 percent of Bruindese lives under poverty line (1.25 $ per day); 13 percent of South African lives under poverty line;
- the ratio of girls to boys in primary and secondary school is lowest in Niger (78 percent) and highest in Cape Verde (104 percent);
- 162 per 1000 infants under five years old die in Sierra Leone, 48 per 1000 infants die in Botswana;
- ratio of private sector credit to GDP is 62.1 percent for Cape Verde economy and 145 percent for South African economy (World Bank, 2013).

In short, concerning economic development, the problems are diverse and the intervention process is complex due to the interaction of the policies.

Different characteristics of market institutions in Africa make intervention process even more complex (see Fafchamps (2004) for a detailed overview of market institutions at the region). African markets are mainly characterized by subsistence production, self-employed entrepreneurs, many small volume transactions, flea markets, relationship based trade contracts, and gift exchange for social insurance. In these markets, judicial systems to regulate the transactions are weak; social institutions and norms such as social networks, customs, personal trust, and reciprocity replace them to sustain cooperation between agents and secure the contract compliance in the exchanges. On contrary, mainly facilitated by strong formal institutions (i.e. judicial system and courts), Western markets possess different characteristics: high specialization in production, high volume per transaction, large enterprises and organizations, developed public and private social insurance schemes, trade through contractual agreements. If the interventions disregard these differences and directly transfer technology and institutions from developed economies to African markets, they may not produce desired outcomes; the transferred innovations may clash with the substitutes in the African markets - which are functional and efficient given the existing market institutions in the region. Moreover, they may also not be as beneficial as they were in their source economies while strong formal institutions are absent but strong social norms and institutions are present. So development interventions must not only focus on interaction between diverse problems of African economies but also consider the unique features of market institutions in Africa.

1.2 Objective and research questions

Studies concerning how broad development interventions affect each African community's economic development and how they interact with each other and market institutions in Africa are steps towards understanding this complex relationship; they therefore have the potential to guide the policy makers in the right direction. The purpose of this dissertation is to add to such studies by analysing the interaction between economic development in Africa and three economic concepts: *decentralized agricultural innovation systems*, *trust* and *saving practices* - all of which are closely related to market institutions in Africa. The aim is not to provide a complete picture of the interactions between those concepts though. Instead each chapter has a stand-alone contribution as a result of separate and independent academic studies.

Specifically this study answers three research questions. The first question concerns the interaction between economic development and agricultural decentralized innovation systems. Several programs and organizations have recently introduced the innovation systems approach to rural Africa via so called innovation platforms in order to stimulate agricultural development in Africa. Innovation system approach does not involve direct transfer of agricultural technologies from developed world to promote rural economic development as conventional approaches do through extension agents. Instead, bringing local stakeholders such as R&D organizations, advisory services, input suppliers, financial organizations, downstream processing and marketing firms all together, innovation platforms design and apply technological and institutional innovations by utilizing local knowledge, opportunities and institutional environment. This thesis explores *how decentralized innovation systems affect local agricultural development in Africa* in Chapters 2-4.

The second question is related to the interaction between *economic development* and *trust.* Theory suggests that trust, which is an important outcome of market institutions in Africa, fosters economic development thanks to reduced transaction costs and increased specialisation. A virtuous cycle may also materialize if increased specialisation, through increased market integration and economic development, also fosters trust. To shed light on the latter argument, Chapter 5 investigates *the effect of market integration on trust at an early level of economic development*.

The third question is about the interaction between *economic development* and *saving practices*. Access to finance is limited in developing countries; therefore entrepreneurs have to save in order to invest back to their businesses. At the same time, entrepreneurs in Africa save through multiple ways. They keep their savings not only in an official account (i.e. in banks or MFI) – like in Western economies - but they also save by entrusting funds to a moneylender for safekeeping, by hiding them in a secret place, or by giving it other household members, etc. Each of those practices may potentially have different efficiency levels, and therefore may have varying effects on business investments. Chapter 6 studies *how those different saving practices affect the likelihood of reinvestment of business profits and compare their reinvestment efficiency*.

To answer the above summarized research questions, the dissertation utilizes two main data sources and various identification strategies. The first question is investigated by using experimental data from the Sub-Saharan Africa Challenge Program (SSA-CP) which introduced local decentralized innovation systems to rural agricultural communities in 8 African countries.[2] Identification mainly relies on *differences in differences* and *panel data* methodologies. The thesis examines the second question by using a sub-section of SSA-CP dataset, and benefits from detailed survey questions to control for confounding factors and instrumental variable strategies to identify the casual relationship. Finally, the study

[2] We use data from only Lake Kivu region site in this data set in Chapter 2.

answers the third question with the help of a national survey in Tanzania which focuses on micro and small enterprises and collects information on entrepreneurs' saving and reinvestment practices. It makes use of detailed survey questions, and employs instrumental variables strategy to overcome concerns regarding endogeneity.

1.3 Related literature

The thesis mainly relates to three distinct areas within the economic development literature. Studies presented in Chapters 2, 3 and 4 fit into the broad literature that investigates the highly debated role of agriculture in economic development. The early popular economic development models have considered agriculture as an unproductive sector from where resources should be de-allocated away to more productive industries to boost economic growth. In contrast, a parallel literature has argued that, having strong linkages with non-farm sectors, agriculture may be the key for economic development particularly at the early stages of development by enhancing growth in rural non-farm economy and leading to faster overall growth (see Christiansen et al. (2010) for a more detailed literature review). Recent studies support the latter argument by showing that the growth in agriculture is better at reducing extreme poverty than non-agriculture sectors (World Bank, 2007; Christiansen et al., 2010; Janvry and Sadoulet, 2010). These findings imply that agriculture may play an important role in tackling poverty in Africa since it is the main source of income for the poor in rural Africa (World Bank, 2007), and there is a large room for increasing production in Africa by improving productivity and land use (Janvry & Sadoulet, 2010). Hence, there is an opportunity to reduce poverty and boost economic development in Africa by enhancing agricultural productivity, land use, and production.

Therefore, many studies have explored the bottleneck points for low productivity and land use in African agriculture (see Binswanger and Kalla (2010) for an overview), and assessed whether wide ranging related policies might solve those bottlenecks. [3] Nevertheless, the literature still lacks quantitative studies evaluating how, within the

[3] Some of the important policy evaluation studies are conducted on access to markets by Barrett (2008); fertilizer use by Duflo et al. (2008); land rights by Goldstein and Udry (2008); new technology usage by Conley and Udry (2010).

institutional frameworks of value chain and agricultural innovation systems, multi-stakeholder development partnerships between various stakeholders affect the adoption of agricultural innovations and development in Africa (Byerlee & Bernstein, 2013; Campell, 2013). Chapters 1, 2 and 3 add to this literature by providing evidence regarding the impact of such a partnership within the framework of decentralized innovation systems on poverty and agricultural innovation.

Chapter 5 contributes to the literature by investigating the interaction between economic development and social capital. Putnam et al. (1994) define social capital as "… features of social organisation, such as trust, norms and networks that can improve the efficiency of society by facilitating coordinated actions" (p. 167). How do those features of social organizations affect economic development? In his seminal work, Putnam et al. (1994) shows that denser social networks and higher social capital explain the differences in industrialization level across Italian regions. Subsequent studies support this finding by showing that social capital of the societies determines the range of economic concepts concerning development (see Guiso et al. 2010 for an overview). Hence, we have enough evidence to argue that social capital is a determinant of the economic development.

On the contrary, much less is known regarding how social capital evolves during the process of economic developments. In one of the rare studies, Miguel et al. (2006) document that during the industrialization process of Indonesia, participation to social groups and interaction with others have increased in the districts of Indonesia. Tabellini (2008) theoretically shows that the increase in those social interactions between socially distant individuals may lead to evolution of generalized moralities which can sustain cooperation between anonymous agents and facilitate trade between them. Inspiring work of Henrich et al. (2004, 2010) confirm the robustness of these theoretical propositions by showing that market friendly social norms may evolve as a result of market integration communities. By using data from behavioral experiments conducted in 14 rural societies, Henrich et al. (2004, 2010) document that there is a positive correlation between the level of market integration of the societies and the prevalence of market friendly behavior such as generalized trust, fairness and cooperation in those societies. This finding may suggest that economic development process lead to the emergence of favourable social norms through market integration of societies, as transformation from personalized exchange to impersonal market exchange is a necessary stage for economic development (Fafchamps 2011). Empirical evidence concerning market integration and evolution of generalized social norms is still limited though; communities subject to former analysis are very heterogeneous or related studies do not estimate a causal relationship from market integration to social norms. Chapter 5 adds to this literature by reporting estimates for the causal effect of market integration on trust from a rural homogeneous society in Western Africa.

Finally, the results presented in Chapter 6 are mainly related to the literature exploring the role of finance in economic development. There is a rich literature showing that development of financial markets matter for economic growth. Those studies have documented that access to financial services such as credit, insurance, payments/money transfer, bank and saving accounts) may alter consumption, investment and saving behavior, and as a result yield to long-term economic growth (see Levine (2005) for a detailed overview). So, can access to similar services in developing countries - where financial markets are usually missing - boost economic development and alleviate poverty as well? To probe this question, recent country level empirical studies have evaluated the impact of financial services such as micro credit, micro insurance and savings products, which are generally designed for the poor households, entrepreneurs and farmers, on several outcomes. For instance, a large literature has studied the impact of micro credit on business performances of entrepreneurs, household income, and consumption in developing countries (see Armendáriz and Morduch (2005) for detailed overview). Cai et al. (2012) and Cole et al. (2013) provide evidence concerning the impact of micro insurance on production choices of farmers in south western China and India respectively. Finally a growing body of literature has assessed the effect of access to formal saving services such as deposit or MFI accounts and informal saving practices such as saving through groups, in a coin container, rotating savings and credit associations, etc. on entrepreneurial decisions, household expenditures and income (see Karlan et al. (2013) for an overview). Chapter 6 mainly contributes to this final literature by comparing the efficiency of those formal and informal saving practices in directing profits back to business investments.

1.4 Outline of the thesis

The thesis is organized as follows. Chapters 2, 3 and 4 focus on the impact of decentralized innovation systems approach on resource poor farmers. Specifically, Chapter 2 evaluates the impact of the innovation systems on poverty and investigates whether it outperforms conventional extension approaches by using experimental data from Central Africa. Chapter 3 investigates whether innovation systems can promote the adoption of agricultural innovations by using experimental data collected in 8 African countries. These two chapters and other related studies in the literature find considerable heterogeneity in the impact of innovation systems; therefore Chapter 4 investigates whether this heterogeneity results from the heterogeneity in implementation of innovation system approach by quantifying the defining principles of the approach into an index.

Chapter 5 examines the impact of increased market integration on various measures of trust. Using a comprehensive survey of households in West Africa which are still in the early stages of market integration, the study identifies a negative and causal relationship between market integration and trust.

Finally Chapter 6 investigates the relationship between entrepreneurial saving practices and reinvestment. This study develops a model of entrepreneurial reinvestment and saving practices and shows that an entrepreneur's reinvestment decision depends on the efficiency of her saving practice, in addition to the productivity and the borrowing capacity of the entrepreneur. Then, utilizing a novel micro and small enterprise survey from Tanzania, the study tests the empirical implications of this theory.

Chapter 2

Decentralized innovation systems and poverty reduction: Experimental evidence from Central Africa[⊥]

2.1 Introduction

Agricultural development in Africa has resurfaced as a priority issue on the international development agenda. In addition to obvious concerns about food security and prices, three factors are responsible for the recent re-appraisal of African farming: targeting, comparative advantage, and inter-sectoral linkages. Some 75% of the poor in developing countries live in rural areas, and the majority of them depend on agriculture for their livelihoods. Given agriculture's dominant role in the lives of the rural poor, it makes sense to center strategies for cutting poverty on growth in this sector (World Bank, 2007). Moreover, most African countries are agriculture-based, and tend to have a comparative advantage in the production of primary commodities. Finally, agricultural growth has large multiplier effects in early stages of development (Haggblade et al. 2007). The growth in GDP originating in agriculture raises incomes of the poor much more than growth originating elsewhere in the economy (Ligon & Sadoulet, 2007), especially for the poorest and especially in early stages of development (Christiaensen et al., 2010).

African rural society is characterised by high transaction costs and risk, hampered information flows, and a weak institutional environment. As a result, both market

[⊥] This Chapter is based on following research paper: Pamuk, H., Bulte, E., Adekunle, A., & Diagne, A. (2014). Decentralised innovation systems and poverty reduction: experimental evidence from Central Africa. *European Review of Agricultural Economics*, jbu007.

development and access to existing markets are inhibited. Creating an enabling institutional and policy environment is a necessary condition for African farming to take-off (IFPRI, 2010). Therefore, the new development agenda emphasizes (*i*) linking farmers to input and output markets, (*ii*) identifying governance arrangements to strengthen property rights and asset control, and (*iii*) promoting technical innovation and diffusion of knowledge to increase land and labour productivity (Djurfeld et al. 2006, World Bank, 2007 Dorward et al. 2009, and IFPRI 2010). Increasingly it is recognized that these elements hang together, and that innovation in the domains of governance and technology could go hand-in-hand.

Agricultural innovation among African smallholders has progressed slowly, and efforts to promote the adoption of new technologies, even if occasionally successful locally, have largely proven unsuccessful. A challenging perspective of conventional, top-down approaches to extension argues that agricultural research should be embedded in a larger "innovation system," integrating knowledge from various actors and stakeholders. This amounts to a participatory approach to innovation and diffusion, which implies a shift from viewing innovation as a "product to a process" (Knickel et al. 2009). In such an innovation system, agents such as firms, research institutes, intermediaries, customers, authorities, and financial organizations are interacting partners resulting in non-linear, iterative processes (Geels 2004, van Mierlo et al. 2010).

The main objective of this study is to compare the performance of traditional "top-down" approaches to innovation and extension to the performance of a decentralized innovation system approach, and to compare both approaches to the default case of doing nothing. Specifically, we focus on the impact of so-called innovation platforms (IPs) on the alleviation of rural poverty and on food consumption. We also probe potential channels explaining impact, focusing on the adoption of specific technological and institutional innovations.

The question whether decentralized, local approaches to extension outperform centralised, top-down ones links to a broader debate that goes back to at least Scott (1989). Scott argues that centrally managed and highly schematic development visions do violence to complex local interdependencies, and systematically fail to achieve their objectives. As an alternative to such "high-modernist" ideologies, based on epistemic knowledge, he proposes greater emphasis on local, practical knowledge (which he labels "metis"). From a theoretical perspective it is not obvious which approach to innovation is more efficient and effective—the traditional, centralized model or the local and participatory model. Economies of scale in innovation and transfer may imply greater benefits for the centralized approach. In contrast, the decentralized approach is presumably better able to capitalize on local knowledge about constraints and possibilities, and local understanding of needs and priorities.

Local institutions, such as the ones that facilitate capitalizing on local knowledge, tend to co-evolve with communities, and respond to local regulatory or cultural issues. In models explaining economic performance based on observational data, local institutions are likely to be endogenous. Careful econometric analysis, based on propensity score matching or instrumental variable strategies,[4] may enable the analyst to attenuate these endogeneity concerns (even if some concerns will remain due to unobserved heterogeneity). An alternative approach to probe the causal impact of institutional innovations is to introduce variation in these institutions—as part of an experiment. This is the approach taken in this paper. Our identification strategy is based on quasi-experimental data obtained in the Sub Sahara African Challenge Program (SSA CP). In a sample of villages in selected countries, IPs were introduced—forums where local stakeholders come together and search for practical ways to advance their livelihoods. We analyse how poverty in these IP villages compares to outcomes in communities served by the traditional innovation approach, and to outcomes in a sample of control villages.

Three remarks are in order. First, our data do not derive from a full-fledged randomized control trial (RCT). The intervention villages were not randomly drawn from the same sample as the control villages (but an effort was made to ensure that the treated and control villages were "similar"). This has implications for the data analysis. Second,

[4] For example, Mapila et al. (2011) uses propensity score matching to investigate the impact of agricultural innovation systems on rural livelihoods in Malawi. They conclude innovation systems increased the rural income, upland crop production and fertilizer use.

IPs were introduced in 2008 and 2009, and follow-up data was collected in 2010. Hence, we can only pick up short-term effects. Future work, based on additional data to be collected in the future (in 2014), should explore whether the results we obtain are sustainable, or are overtaken by other events, and explore whether the channels via which IPs have impact on poverty evolve over time. Third, although the program involves a cost, we do not have any data regarding the amount of the cost. Only if we find that the intervention does not reduce poverty, we can reach to a conclusion about its cost efficiency and conclude that it is inefficient.

We obtain a nuanced set of results. On average, the decentralized innovation systems approach is better able to alleviate poverty than the traditional approach (and both approaches are better than doing nothing). However, we also document considerable heterogeneity across IPs. There are successful IPs as well as unsuccessful ones in terms of poverty alleviation, and it appears as if some of the platforms have failed to engage the relevant stakeholders, or have otherwise been unable to mobilize stocks of local knowledge. Unearthing the determinants of IP performance is left as an urgent priority for future research.

The paper is organized as follows. In section 2.2 we briefly summarize key lessons from the literature on agricultural innovations in Africa. In section 2.3 we describe the Sub Sahara African Challenge Program, and the nature of its main intervention—the creation of innovation platforms in selected villages. In section 2.4 and 2.5 we summarize our data and outline our identification strategy, respectively. Section 2.6 presents the results, focusing on average poverty impacts of the innovation system approach and on heterogeneous treatment effects (across innovation platforms and across individuals treated by the same platform). In section 2.7 we probe the channels linking IPs to reduced poverty, and section 2.8 concludes.

2.2 Agricultural innovations in Africa

Agricultural yields in many African countries have been declining in recent decades. One reason for this disappointing outcome is imperfect adoption of innovations. Agricultural innovations may be a significant growth factor for the economy as a whole, via effects on demands for inputs and prices of food (see the recent paper on mechanisation in US farming by Steckel and White 2012). While various yield-increasing technologies are available for African farmers, their uptake among smallholders remains far below 100%. Key factors identified in the literature include factors directly linked to the technology (availability or untimely delivery of innovations, high costs, demands on complementary inputs, "riskiness"), factors at the level of individual farmers (e.g., education, access to credit, but also risk preferences and loss aversion—see Liu 2013), and contextual factors such as poor extension, transaction costs (e.g., bad infrastructure), access to value chains (Barrett et al. 2012), and geophysical conditions (for discussions, refer to Feder et al. (1985), Rogers (1995), Sunding and Zilberman (2001), and Suri (2011)). Recent academic work emphasizes the role of social learning and networks in innovation and diffusion processes (e.g., Bandiera & Rasul (2006) and Conley & Udry (2009)).

Some analysts argue that an important cause of the limited impact of traditional research and extension activities in Africa is the simplistic yet dominant view on innovation processes (Leeuwis & van de Ban 2004). According to the traditional adoption and diffusion model (or pipe-line model, sometimes referred to as technology-transfer model, delivery model, or technology-push model) innovation is conceptualized as a linear process. It starts with conception by scientists and extends to adoption by farmers, via extension workers (Knickel et al. 2009). Research, transfer, and adoption are independent activities, and there is little attention for the context within which these processes are embedded.

Consequently, traditional extension — for which various modalities exist, including the well-known training and visit (T&V) and village agent model — often amounted to "blanket recommendations." Such recommendations might not fit with local conditions. For example, heterogeneity in returns to new technology has recently been documented by Duflo et al. (2008) for the case of fertilizer, and by Suri (2011) for the case of hybrid maize. The lack of a fit between recommended technologies and local needs may be especially pronounced when research and extension are biased towards big farmers. Not surprisingly, then, demand for extension may be weak among food producing smallholders in peripheral locations (Holmen 2005). There are additional reasons for pessimism about the effectiveness of traditional extension. "Public services have dominated extension. … But public financing and provision face profound problems of incentives of civil servants for accountability to their clients, weak political commitments to extension, extension workers not being abreast of relevant emerging technological and other developments, a severe lack of fiscal sustainability in many countries, and weak evidence of impact" (World Bank, 2007, p.173).

In fairness, the traditional approach to extension is gradually changing, shifting from the prescription of technological practices to focusing on capacity building among rural people – empowering them (World Bank, 2007). Accordingly, extension efforts now sometimes include a broader range of approaches, including public-private partnerships (collaboration between state, firms and NGOs) and farmer-to-farmer training. However, conventional extension in our study region is still characterized by a single line of command, based on "expert knowledge" flowing to farmers through a network of public extension agents. We seek to explore whether participatory approaches to innovation and diffusion, and specifically agricultural innovation systems, - are more or less successful in reducing rural poverty in our study region.

The theory defines agricultural innovation systems as informal organizational structures including various stakeholders (e.g. farmers, research institutes, NGOs, etc.) and aiming to increase agricultural production by facilitating the communication between stakeholders and design of local agricultural innovations (see Geels 2004 for a detailed discussion on innovation systems theory.). The theory hypothesize that innovation systems may increase the success chance of agricultural innovations by making the participation of the farmers to the innovation research process easier and serving as a feedback mechanism. Though their participation, local farmers may share their tacit knowledge of local farming characteristics in the agricultural research process; this enhances the likelihood of the match between local needs and outcome of the research - the innovations that will be promoted in the field. Participation may also boost their understanding of promoted innovations, thereby increasing the likelihood of adoption in the field. Finally, innovation systems serve as a feedback mechanism through which producers can report the problems concerning the innovations. Hence policy makers can re-design and re-introduce innovation according to the received feedback and make sure that innovations have been proved useful for the producers and adapted by them. .

2.3 Program description: Introducing innovation systems in African farming

We test the hypothesis above by utilizing the SSA CP started in 2004. To remedy perceived problems with the traditional approach to extension, a new approach was proposed named Integrated Agricultural Research for Development (IAR4D). It aims to bring stakeholders together and integrate their knowledge so as to generate network effects and stimulate innovation relevant for the local context. The ultimate objective is to alleviate rural poverty.

The IAR4D approach aims to promote innovations via decentralized innovation systems, so called IPs. IPs are introduced in selected locations (serving various villages), and serve as vehicles to bring together representatives of farmers' associations, private firms and traders, researchers, extension workers, NGOs, and government policy makers. Ideally, an IP should decide on membership of stakeholder groups through a participatory and bottom up process. Selected stakeholders should come together, diagnose common challenges and bottlenecks, and decide on strategies to overcome key problems. This includes raising awareness among local communities for adopting the innovations prioritized in the action plan—assigned IP members go to the field and facilitate adoption (FARA, 2008).[5] To facilitate the adoption, IPs may implement the education programs for the communities, give information to farmers regarding agricultural techniques, and provide extension services. How these have been implemented, and which institutional and technological innovations an IP have focused on may vary between IPs. Because IPs operate at the local level, responding to local challenges, they are independent of each other, and each IP follows its own agenda under the general framework of IAR4D approach. For this reason, across IPs the diagnosis and strategy setting stages may produce

[5] However, there is always a risk that IPs might not function ideally. For instance, some stakeholders might promote the adoption of specific innovations before other stakeholders have decided on the bottlenecks.

different outcomes. Importantly for the purposes of this evaluation the intervention did *not* include subsidized access to certain inputs, loans (which would otherwise have confounded the poverty impact of the institutional innovation).

The Forum for Agricultural Research in Africa (FARA) coordinated the implementation of the SSA CP through local partner agencies (NGOs and universities)[6], and aimed to investigate IAR4D's effectiveness relative to doing nothing and conventional research and extension approaches. For the latter purpose, the implementation plan was designed as an experiment. The objective was to obtain results informative about agricultural development across the African continent, hence the program was rolled out in three major sub-regions (so-called project learning sites: PLS): (*i*) "Lake Kivu" in Eastern and Central Africa, (*ii*) "Kano-Katsina-Maradi" in West Africa, and (*iii*) Zimbabwe-Malawi-Mozambique in Southern Africa. In total, 36 IPs were created—12 per PLS. An IP serves multiple intervention villages (typically between 5 and 10 villages, so the number of treated villages was expected to be between 60 and 120 villages per PLS). Per village, 10 households were randomly sampled and surveyed, so the total number of households surveyed per PLS is in the range of 600-1,200. To evaluate the performance of IAR4D villages, data were also collected in two types of comparison villages (conventional extension villages and control villages without any intervention – see below). The total number of respondents per PLS is therefore in the range of 1,800-3,600.

How were intervention and control villages selected? The selection has been done by the local project implementation teams consists of local stakeholders at each PLS. The details of the sampling procedure vary slightly across PLSs. As poverty data for midline period (see below for details) are collected at Lake Kivu PLS only, we use data from the Lake Kivu region, capturing parts of Uganda, Rwanda and the Democratic Republic of Congo (DRC) for the analysis. In each country, a sample of *sites* or *wards* was selected (named *sub-counties* in Uganda, *secteurs* in Rwanda, and *groupements* in the DRC). These wards represent administrative groupings of multiple villages, and were selected to provide

[6] The funds FARA received from international donors have been allocated to local agencies and local agencies used these funds to implement the project.

a representative sample in terms of market access and agro-ecological conditions. In total, 24 wards are included in the Lake Kivu PLS, evenly split across the three countries.

When designing the study, a trade-off had to be struck between the management of spill-over effects (e.g., counterfactual villages benefitting from activities or ideas generated at nearby platforms) and the balance of the sample. If treatment status would be randomly assigned at the village level, then treatment and counterfactual villages are expected to be similar at the baseline, both in terms of observables and unobservables. But random assignment at the village level also implies that treated villages may be located next to counterfactual villages. To attenuate potential spill-over bias, assignment into treatment was done at the level of the ward. This implies treated and counterfactual villages are clustered in space, minimizing spill-over effects—a benefit that comes at the cost of reduced balance between treated and counterfactual villages (as will be evident below).

12 wards were assigned to receive the treatment, and consequently a random subsample of (clean) villages from these wards received an IP. We define “clean villages” as villages that did not receive any (conventional) projects in the 5 years preceding the intervention (i.e. no extension or NGO activities during the period 2003-2008). The other twelve wards were assigned to control status, and a random sample of villages from these wards comprises our samples of counterfactual villages. Specifically, villages from these “control wards” were assessed and classified into one of 2 types of villages: (*i*) clean villages that had neither received IAR4D nor conventional projects in the previous 2-5 years; and (*ii*) conventional extension villages, which had received projects identifying, promoting and disseminating technologies in the same period. Hence, based on their individual history of exposure to extension, some villages drawn from the control wards were labelled as “control (clean) villages,” and others as “conventional (extension) control villages.”

It is important to note that the historical allocation of extension workers across the African landscape is possibly non-random. Hence, we need to delve into selection issues and potential endogeneities, when assessing the impact of innovation platforms. Details of our identification strategy are discussed in section 2.5.

2.4 Data

We use data from the Lake Kivu PLS containing villages in the Democratic Republic of Congo (DRC), Rwanda and Uganda. For this site, 76 villages were randomly selected to be "treated" by IAR4D (i.e., received an IP). There was no non-compliance – all villages accepted the IP (but there is variation in the nature of the intervention across sites; see below). A village census was carried out in adjacent wards to construct a sample frame and stratify villages into the sets of "(clean) control" and "(conventional) extension" villages. Next, 85 villages were drawn from the set of control villages, and another 85 villages were drawn from the set of traditional extension villages. Note that control and conventional extension villages were drawn from the same 12 wards, and that these wards are not the same as the ones from which the IAR4D villages were selected.

Baseline data were collected in the DRC, Rwanda and Uganda in 2008/09, and the next wave of data was collected in 2010. Since some of the baseline data are collected in late 2008 and others in early 2009, we control for the timing of data collection via a dummy variable. Over both surveys we observe some 2,230 households, residing in 244 villages (indicating some attrition as the number of respondents in the baseline wave was 2,402). The average number of respondents per village was 9.5 (standard deviation 1.6). A summary of the sampling frame is provided in Table 2.1.[7]

Table 2.1: Sample design

Survey	Control	Conventional	IAR4D (intervention)	Total
Households				
baseline	806	816	780	2,402
midline	769	776	685	2,230
Villages				
baseline	85	85	76	246
midline	84	85	75	244

[7] One reason for attrition was oversampling at the baseline. At the baseline, we slightly oversampled villages and households in Rwanda. Subsequently, one village (Remera) was randomly dropped from the analysis. Moreover, 44 households were randomly dropped from other oversampled villages as well. One other village in the DRC could not be visited because of security concerns. A reason for remaining attrition is "relocation" of the respondent. The analysis below is based on less than 2230 households because of missing values in either the base- or midline controls. However, we have also estimated the key models based on parsimonious specifications (fewer controls, more observations) and the results are very similar.

Table 2.2 summarizes our outcome variables. These include innovation proxies (as intermediate outputs) and two poverty indicators. As poverty indicators, we use the commonly used headcount ratio (measured at the village level) as our primary measure, and a less-standard household-level Food Consumption Score (FCS). Our poverty rate estimate is not based on census income data, but represents an estimate provided by the village leader and several other local "leaders" (including school teachers, etc.). During a focus group discussion[8], these leaders tried to reach a consensus regarding the number of households below the poverty line.[9] Poverty was defined as per capita income below USD 1.25. We discuss potential shortcomings of this variable in the final section.

The FCS index is based on daily food consumption of respondents during a short interval of time, corrected for the nutritional value of food items consumed.[10] It is well known that such measures may fluctuate over the seasons. However, since our data were collected in treatment and comparison villages simultaneously, we are able to control for such seasonal influences in our empirical analysis.[11]

[8]The village leader, some selected farmers from the village and local project stakeholders from government, universities, research institutes, etc. attended to the focus group meeting at each village. In the meetings, the project officers asked pre-determined questions concerning village characteristics (landscape, institutions, organizations etc.), whether there have been any previous extension efforts in the village, and whether villagers are willing to participate to the project.

[9] While we appreciate the potential concern that focus-group estimates of local poverty may be less than perfect, we believe it is fair to say that household poverty data are typically also imperfect – obtaining reliable income data is notoriously difficult, which is why the Challenge Program opted for the focus group methodology. Note, that the focus group data are available in panel format (for both treated and control groups) so systematic errors in measurement should not concern us.

[10] To construct this index we used information about household consumption of certain groups of food during the last 30 days and converting it to weekly by calucating the corresponding level for 7 days. Food groups are: Cereals, vitamin rich vegetables and tubers, white tubers and roots, dark green leafy vegetables, other vegetables, vitamin a rich fruits and other fruits, meat, eggs, fish, legumes, nuts and seeds, milk and milk products, oils and fats, sweets, spices, caffeine or alcoholic beverages. We score each food group based on the World Food Program Technical Guidance Sheet for Food Consumption Score (UN 2008). Scores increase with the nutrition level of the food group, and the index score for each household is calculated by summing group scores.

[11] Specifically, our estimates of the impact of the intervention relative to the control and conventional extension villages will be unaffected if all types of villages respond the same way to seasonal fluctuations.

Table 2.2: Outcome (dependent) variable definitions

Variable	Definition
Poverty indicators	
Headcount ratio	percentage of the people living under poverty line
FCS	Food consumption score, calorie weighted average of weekly consumption of a respondent
Technology indicators	
Mulching	equals 1 if a household uses mulching , 0 otherwise
Trenches/terraces	equals 1 if a household uses trenches/terraces, 0 otherwise
Water harvesting	equals 1 if a household uses water harvesting, 0 otherwise
Irrigation	equals 1 if a household uses irrigation techniques, 0 otherwise
Conservation farming	equals 1 if a household uses conservation farming, 0 otherwise
Animal manure	equals 1 if a household uses animal manure 0 otherwise
Cover crops	equals 1 if a household uses cover crops, 0 otherwise
Crop rotation	equals 1 if a household uses crop rotation, 0 otherwise
Inter cropping	equals 1 if a household uses inter cropping, 0 otherwise
Rhizobiainoculation	equals 1 if a household uses Rhizobiainoculation , 0 otherwise
Chemical fertilizer	equals 1 if a household uses chemical fertilizer , 0 otherwise
Row planting	equals 1 if a household uses row planting , 0 otherwise
Plant spacing	equals 1 if a household uses plant spacing, 0 otherwise
Organic pesticide	equals 1 if a household uses organic pesticide, 0 otherwise
Inorganic pesticide	equals 1 if a household uses inorganic pesticide, 0 otherwise
Drying	equals 1 if a household uses drying, 0 otherwise
Threshing/shelling	equals 1 if a household uses threshing shelling equipment, 0 otherwise
Improved storage facil.	equals 1 if a household uses improved storage facilities, 0 otherwise
Pest control	equals 1 if a household uses pest control, 0 otherwise
Grading	equals 1 if a household uses grading, 0 otherwise
Land regulation	
Nrmbylaws	equals 1 if the local council in the village enacted any bylaws related with natural resource management, 0 otherwise
Landbylaws	equals 1 if there any bylaws affecting land management in the village, 0 otherwise
Marketing strategies	
Notsold	equals 1 if household did not sell at least one type of product it produced, 0 otherwise
Consumers	equals 1 if household sold at least one type of product on farm to consumers, 0 otherwise
Middleman	equals 1 if household sold at least one type of product on farm to middleman, 0 otherwise
On the roadside	equals 1 if household sold at least one type of product on the road side, 0 otherwise
local market	equals 1 if household sold at least one type of product at the local/village market, 0 otherwise
district town	equals 1 if household sold at least one type of product at the district town market, 0 otherwise
distant market	equals 1 if household sold at least one type of product at a distant market, 0 otherwise
Sold	equals 1 if household sold at least one type of product it produced, 0 otherwise
Village Resources	
Wells	equals 1 if the village have boreholes/wells, 0 otherwise
Veterinary	equals 1 if the village have cattle dips/veterinary, 0 otherwise
Woodlots	equals 1 if the village have village woodlots, 0 otherwise
Water body	equals 1 if the village have water bodies, 0 otherwise
Watering points	equals 1 if the village have livestock watering points

Table 2.3: Variable definitions for control variables

Variable	Definition
Household characteristics	
edu_primary	equals 1 if household member having highest education level at most have completed primary school, 0 otherwise
edu_ secondary	equals 1 if household member having highest education level at least have some vocational training and at most have completed secondary education, 0 otherwise
edu_univer	equals 1 if household member having highest education level at least have attended to a college and at most have completed a university, 0 otherwise
Gender	equals 1 if household head is male
Hhsize	number of persons living in the household
duration	number of years of experience in farming of household head
age 15-24	equals1 if age of the household head between 15 and 24, 0 otherwise
age 25-34	equals1 if age of the household head between 25 and 34, 0 otherwise
age 35-44	equals1 if age of the household head between 35 and 44, 0 otherwise
age 45-54	equals1 if age of the household head between 45 and 54, 0 otherwise
age 55-64	equals1 if age of the household head between 55 and 64, 0 otherwise
age 65+	equals1 if age of the household head is above 65, 0 otherwise
dependency	ratio of the number of household members aged below 16 and above 64 to the number of members aged between 16 and 64.
borrowed_ formal	equals 1 if household borrowed from bank or micro or government credit schemes credit institutions, 0 otherwise
borrowed_informal	equals 1 if household borrowed from informal savings, money lender, NGO/Church, relatives , 0 otherwise
rooms1	equals 1 if household lives in a house having no rooms or 1 room, 0 otherwise
rooms2	equals 1 if household lives in a house having 2 rooms, 0 otherwise
rooms3	equals 1 if household lives in a house having 3 rooms, 0 otherwise
rooms4	equals 1 if household lives in a house having 4 rooms, 0 otherwise
rooms5	equals 1 if household lives in a house having 5 or more rooms, 0 otherwise
survey time	equals 1 if baseline of survey is applied in 2009, 0 if it is applied in 2008
Village Characteristics	
School	equals 1 if the village have schools, 0 otherwise
Hospital	equals 1 if the village have hospitals/clinic/health, 0 otherwise
Telephone	equals 1 if the village have telephones, 0 otherwise
Roads	equals 1 if the village have all weather roads passing, 0 otherwise
Country1	equals 1 if the village is in Democratic Republic of Congo, 0 otherwise
Country2	equals 1 if the village is in Rwanda, 0 otherwise
Country3	equals 1 if the village is in Uganda, 0 otherwise

We distinguish between 4 different categories of innovation variables: technology indicators, marketing strategies, access to village resources, and land regulations. Hence, following van der Ploeg et al. (2004) and Pamuk et al. (2014b) we interpret “innovation” quite broadly, encompassing technologies as well as governance arrangements, the adoption of new regulations, changes in market participation practices, or access to new infrastructure. Unlike the adoption of techniques, we treat institutional or access innovations as community variables—common to all households in the village.

Finally, our control variables are summarized in Table 2.3.We distinguish between household and village characteristics. While we focus on village variables, the household variables allow us to analyse heterogeneous impact across various dimensions, and test for potential selection bias (e.g., education, gender, household structure and wealth, farming practice, access to credit, community development). As mentioned, we also created a survey time dummy, capturing whether the household was first surveyed in 2008 or 2009.

2.4.1 Testing for balance

Since the IAR4D and counterfactual villages were not randomly selected from the (same) population of villages it is imperative to check how the three groups of villages compare at the baseline. Table 2.4 compares control, conventional and IAR4D villages in terms of dependent variables and (household and village) controls. The first three columns provide sub-group averages for the various variables, and the other three columns test whether observed differences are significant, or not.

While there are neither significant differences in poverty variables between conventional extension and control villages, nor between the IAR4D and conventional extension villages, we do observe that on average the number of poor people in IAR4D villages is higher than in control villages. Failing to account for such pre-existing differences will bias impact assessments. In terms of food consumption, we do not measure significant differences across the three types of villages.

In terms of our household controls, there are hardly any differences between the three types of villages. It appears as if the number of respondents with secondary education is somewhat smaller in IAR4D villages than in control villages and households living in IAR4D villages have more access to formal credit. But the differences are very small and some random differences are not unexpected given the size of our sample. It is interesting to observe, however, that in terms of household variables there are hardly any differences between the conventional and control villages. We observe that, in conventional villages, average house size is slightly larger, and the number of respondents who completed secondary education is slightly higher than in control villages.

Table 2.4: Mean values for baseline variables

Indicators	Control	Conv.	IAR4D	Conv. - Control	IAR4D - Control	IAR4D – Conv.
			Poverty indicators			
Headcount ratio	43.09	51.82	56.45	8.73	13.36**	4.63
FCS	39.43	40.51	39.74	1.08	0.31	-0.77
			Household characteristics			
Gender	0.79	0.82	0.82	0.03	0.02	-0.01
age 15-24	0.05	0.06	0.06	0.01	0.00	0.00
age 25-34	0.20	0.20	0.22	0.00	0.02	0.02
age 35-44	0.25	0.24	0.24	-0.01	-0.01	0.00
age 45-54	0.22	0.24	0.23	0.02	0.01	-0.02
age 55-64	0.15	0.13	0.15	-0.02	0.00	0.01
Hhsize	6.55	6.74	6.37	0.19	-0.17	-0.36*
edu_secondary	0.33	0.33	0.26	0.00	-0.07**	-0.07**
edu_univer	0.05	0.08	0.06	0.03	0.01	-0.02
Dependency	1.34	1.31	1.30	-0.03**	-0.04	-0.01
rooms1	0.06	0.04	0.04	-0.02	-0.02*	0.00
rooms2	0.16	0.13	0.13	-0.03	-0.03	0.00
rooms3	0.24	0.25	0.27	0.00	0.02	0.02
rooms4	0.33	0.33	0.35	0.00	0.01	0.02
rooms5	0.21	0.26	0.22	0.05*	0.01	-0.04
borrowed_formal	0.03	0.04	0.06	0.01	0.03*	0.02
borrowed_infor.	0.64	0.68	0.68	0.03	0.03	0.00
Duration	22.43	22.06	21.40	-0.37	-1.03	-0.65
			Village characteristics			
School	0.48	0.44	0.47	-0.04	0.00	0.03
Hospital	0.13	0.20	0.12	0.07	-0.02	-0.08
Telephone	0.52	0.49	0.53	-0.03	0.00	0.04
Roads	0.45	0.51	0.59	0.07	0.14*	0.08
survtime	0.29	0.29	0.20	0.00	0.09	-0.09
country1	0.35	0.35	0.26	0.00	-0.09	-0.09
country2	0.29	0.29	0.34	0.00	0.05	0.05
country3	0.35	0.35	0.40	0.00	0.04	0.04

Note: * p<0.05, ** p<0.01, *** p<0.001 Standard errors for the differences in household characteristics are calculated by using robust standard errors clustered at village level.

The situation is also similar for village characteristics. When comparing IAR4D villages to control ones, there does not seem to be a systematic bias. The only finding is that IAR4D villages are more likely to be connected via an all-weather road than control villages (so we control for this in the empirical analysis below). We again do not observe any difference between conventional and control villages in terms of observed characteristics. So, if extension workers purposefully selected some villages and not others, it appears as if they are not basing their selection on village characteristics.

2.5 Identification: Average treatment effects and heterogeneous impact

We now outline our identification strategy. We are evaluating the impact of innovation platforms on poverty rates and innovation proxies as intermediate outcome variables. Note that this is not necessarily the same as evaluating the impact of IAR4D on poverty rates. The reason is that there may be non-compliance in the sense that not all IPs function as intended by the IAR4D philosophy. While all treatment villages received their treatment (i.e., they received an IP), the level of stakeholder engagement and bottom-up priority setting may vary from one IP to the next. As an extension of the current analysis, one might develop an index measuring the "degree of IAR4Dness" across the platforms. This would enable the analyst to estimate an IV model using assignment status as an instrumental variable for index scores, and regress poverty and adoption rates on predicted IAR4Dness. Such a strategy would yield a local average treatment effect (LATE) of IAR4D on poverty rates. The current analysis based on a comparison of poverty rates and food security across IP villages and counterfactual villages yields an intent-to-treat (ITT) estimator of the average treatment effect of receiving an IP. In what follows, and slightly abusing terminology, we also refer to this as the ITT of receiving IAR4D treatment.

We seek to gauge impact by comparing IAR4D villages (i.e. villages benefitting from an IP) and either conventional or control villages in terms of reduced poverty. If extension workers selected the set of conventional villages non-randomly, then failing to account for this may introduce selection bias. The literature suggests several ways to accommodate this concern (e.g., Angrist & Pischke, 2009; Imbens & Wooldridge, 2009). We use (*i*) a difference-in-difference (*DD*) methodology that combines aggregate baseline and midline data, and (*ii*) a first difference (panel) methodology, where we base impact assessment on intra-unit comparisons over time. So our analysis depends on the assumption that if there was not IAR4D intervention, the trend in outcome variables would be same for the treatment and control villages. Thus there is heterogeneity in the time varying unobserved factors (to econometrician) between control and IAR4D villages. Since we have only two waves of data, we cannot test whether this assumption holds.

Lack of control over conventional extension activities introduces another problem. By definition, conventional extension activities started *before* the SSA CP started. Hence, conventional villages started receiving their intervention before the IAR4D concept was implemented, and cumulative effort in conventional villages could easily exceed effort in IAR4D villages. This cumulative effect could confound simple comparisons of midline data. However, *ex ante* there is no significant difference in the headcount ratio between conventional and control villages, according to the evidence in Table 2.4. This might simply reflect that conventional approaches to innovation and diffusion have been ineffective.

Another factor may be relevant. Insofar as it takes time to gain momentum and genuinely achieve impact, the deck is stacked against IAR4D—the conventional villages made a flying start at t=0, and, hence, should be able to accomplish more during the interval from t=0 until t=1 (thus, perform superiorly according to the *DD* or panel model). In contrast, if there are diminishing returns to intervention effort, then perhaps the "greenfield" start of IAR4D implies an advantage in a panel setting. The reverse is true in case of increasing returns to intervention effort. These are caveats that should be borne in mind when interpreting the empirical results, but which cannot be addressed rigorously with the data currently at our disposal.

2.5.1 Intention to treat effects

Define outcome variables, which are introduced in Table 2.2, for individual *i*, living at village *v* at time *t* by Y_{0ivt}, Y_{1ivt}, Y_{2ivt} for control (subscript 0), conventional (subscript 1) and intervention/IAR4D treatment groups (subscript 2), respectively. We will drop the *i* subscript for outcome variables at the village level. Treatment groups are denoted by $Control_v$, $Conv_v$ and $IAR4D_v$ for control, conventional and IAR4D villages, respectively.

Treatment dummies are equal to 1 if the household (or village) belongs to that group and 0 otherwise. Since villages can only belong to one treatment group, we know:

(2.1) $Control_v + Conv_v + IAR4D_v = 1$

The simplest analysis rests on a comparison of midline data. Estimates are unbiased if a classical conditional independence assumption holds:

(2.2) $E[Y_{iv}|X_i,Z_v,IAR4D_v,Conv_v] = E[Y_{iv}|X_i,Z_v]$

where X_i refers to a vector of observed household characteristics and Z_v denotes the vector of village level characteristics. Condition (2.2) states that, after controlling for household and village characteristics, the likelihood of being in a control, conventional extension or IAR4D village is same for households. If we also assume there is a linear relationship between outcome and treatment plus other control variables, we can formulate the following regression model:

(2.3) $Y_{iv} = \alpha + \gamma_1\, IAR4D_v + \gamma_2\, Conv_v + \beta'\, \boldsymbol{X}_i + \theta'\, \boldsymbol{Z}_v + \varepsilon_{iv}$

where ε_{iv1} denotes an error term. In (3), γ_1 and γ_2 capture the average treatment effect (ATE) of IAR4D and conventional policies on control villages. To assess ATE of IAR4D approach and whether innovation platforms are more effective than conventional policies, we test whether $\gamma_1 \neq 0$ and $\gamma_1 - \gamma_2 \neq 0$. To ease the analysis process and test the statistical significance of $\gamma_1 - \gamma_2 \neq 0$ directly, we also reformulate (2.3) such that:

(2.4) $Y_{iv} = \alpha + \delta_1\, Control_v + \delta_2\, Conv_v + \beta' \boldsymbol{X}_i + \theta'\, \boldsymbol{Z}_v + \varepsilon_{iv}$

This gives us $-\delta_1 \equiv \gamma_1$ and $-\delta_2 \equiv \gamma_2\text{-}\gamma_1$. However, estimating (2.4) likely produces biased estimates of impact because it is unlikely that the assumption of conditional independence holds. Relaxing this assumption, we now introduce a difference-in-difference model (*DD*) that combines midline and baseline data. With the usual constant trend assumption, we obtain the following model for outcome variable, Y_{ivt}:

(2.5) $Y_{ivt} = \alpha + \mu\, midline_t + \sigma_1\, Control_v + \sigma_2\, Conv_v + \delta_1\, (midline_t \times Control_v) +$

$\delta_2(midline_t \times Conv_v) + \beta'\, \boldsymbol{X}_{it} + \theta'\, \boldsymbol{Z}_{vt} + \varepsilon_{ivt}$

where $midline_t = 1$ if $t=1$ (i.e. for the midline survey), and $midline_t = 0$ otherwise. In equation (2.5), $-\delta_1$ and $-\delta_2$ provide the ATE of innovation platforms on control villages, and the difference between IAR4D and conventional approaches, respectively.

Unobserved heterogeneity at village level may drive the selection of conventional villages and also be correlated with the outcome variable, and therefore may bias the impact estimates in (2.5). Assuming that these unobserved characteristics are constant and separable, the outcome variable can be formulated as follows:

$$(2.6)\quad Y_{ivt} = \alpha_i + \mu\, midline_t + \sigma_1\, Control_v + \sigma_2\, Conv_v + \delta_1\, (midline_t \times Control_v) + \delta_2\, (midline_t \times Conv_v) + \beta'\, \boldsymbol{X}_{it} + \theta'\, \boldsymbol{Z}_{vt} + \varepsilon_{ivt}$$

To eliminate unobserved fixed effects, we use balanced sample of households and first-difference (2.6) so that:

$$(2.7)\quad \Delta Y_{iv1} = \mu + \delta_1\, Control_v + \delta_2\, Conv_v + \beta'\, \Delta\boldsymbol{X}_{it} + \theta'\, \Delta\boldsymbol{Z}_{vt} + \Delta\varepsilon_{ivt}$$

In what follows we will refer to this model as the first difference, or FD, model. The DD and FD models are complementary approaches to dealing with potential selection effects caused by the non-random selection of conventional villages. Models (2.5) and (2.7) are estimated using OLS[12]. In all estimations, we include household and village characteristics summarized in Table 2.3, and the country dummies drops in first difference models.[13] As the headcount ratio indicator, land regulations and village resources variables are available at the level of the village, we estimate models for those variables at the village level, and take unweighted averages of relevant household variables to arrive at village-level variables. Since there may be correlation among households within villages, we cluster

[12] This means we use linear probability models to deal with binary outcomes, allowing ready comparison across specifications. Our specifications should be robust with respect to these commonly used methodologies as most of the covariates are dummy variables. If we assume that treatment heterogeneity is limited, regression estimations are close to the average effects (indeed, fitted probabilities will be between 0 and 1—see section 5 for evidence on heterogeneity). However, we have also estimated non-linear models and our qualitative results do not change much then (even if for two of the innovation indicators different results emerge—estimates available on request).

[13] The estimates are robust when we use only baseline household and village characteristics as control variables for the first difference models.

standard errors at the village level[14], and use robust standard errors (i.e., models explaining food consumption scores).[15] Finally, we note that power of the estimations may be low, as we have observations for a small number of villages. The power tests[16] show that the smallest program effects on poverty and FCS that can be detected with 5 percent statistical significance level are around 12 percentage points and 3.7 points respectively. Therefore when interpreting, we will be cautious regarding the type II errors: to falsely conclude that there is no treatment effect, even if there actually is one.

2.5.2 Tackling heterogeneity

While the average impact of conventional and IAR4D treatments in terms of reduced poverty may be assessed using the above strategy, it ignores that the returns to the treatment may vary across IPs, depending on local circumstances. To probe into this issue we analyse heterogeneity in impact. We take the entire sample of control villages as the counterfactual for each IP (but obtain similar results when using, instead, only control villages from the same country as the IP in question as the counterfactual), and explore how impact varies for the 12 IPs by using the following model: [17]

(2.8) $\Delta Y_{\mathrm{ivt}} = \mu + \delta_1\, Control_{\mathrm{v}} + \Sigma_{\mathrm{ip}}\, \theta_{\mathrm{2ip}} IP_{\mathrm{ip}} + \beta'\, \Delta \boldsymbol{X}_{\mathrm{it}} + \theta'\, \Delta \boldsymbol{Z}_{\mathrm{vt}} + \Delta\varepsilon_{\mathrm{ivt}}$

(2.9) $\Delta Y_{\mathrm{ivt}} = \mu + \delta_2\, Conv_{\mathrm{v}} + \Sigma_{\mathrm{ip}}\, \theta_{\mathrm{1ip}} IP_{\mathrm{ip}} + \beta'\, \Delta \boldsymbol{X}_{\mathrm{it}} + \theta'\, \Delta \boldsymbol{Z}_{\mathrm{vt}} + \Delta\varepsilon_{\mathrm{ivt}}$

where *ip* denotes each IP (*ip* = 1, …12). $IP_{\mathrm{ip}} = 1$ if a household lives in an IAR4D village. If IAR4D has an impact for a specific IP, then $\theta_{\mathrm{1ip}} \neq 0$. Moreover, if $\theta_{\mathrm{2ip}} \neq 0$, then this

[14] The poverty results are robust to clustering the standard errors at IP level.

[15] In theory our estimates could be biased if alternative organisations implemented other interventions systematically targeting IAR4D villages or comparison villages. We have kept track of other interventions in IAR4D villages, and found this hardly occurred. We have no data on other projects in comparison villages. If another organisation specifically targeted our comparison villages and implemented a project that alleviated (enhanced) local poverty, then our DD and FD models will underestimate (overestimate) the true impact of the IAR4D intervention.

[16] We used G*Power program to estimate the post-hoc rminimum impact sizes . In the estimation, sample size, alpha and power is assumed as 16, 0.05, and 0.8. To reach to minimum impact sizes we use standard error estimates from the regression results. The minimum impact sizes are higher for IP level estimations (see below) as degrees of freedom are lower for those models.

[17] We do not aim to estimate the true impact estimate via this analysis since we cannot identify the true counterfactual group for each IP.

impact is different from the effect of the conventional approach. Heterogeneity in terms of impact implies $\theta_{1ip} \neq \theta_{1ip'}$ where $ip \neq ip'$.

Heterogeneity might also materialize at the household, rather than the IP, level. Not all households may be able to benefit from the proposed innovation (e.g., because it does not meet their capabilities, skills, assets, or desires). Indeed, if IPs are hi-jacked to serve the interests of local elites, they could aggravate local inequality. We therefore speculate that the impact of IAR4D might vary with certain household characteristics. To examine whether this is true, we estimate the following model, which is based on (2.7) but includes interaction terms:

$$(2.10)\quad \Delta Y_{ivt} = \mu + \delta_{31}\, IAR4D_v + \varphi'\, (\mathrm{IARD4D}_v \times \mathrm{F}_{it}^{k}) + \delta_2\, Conv_v + \beta'\, \Delta \boldsymbol{X}_{it} + \theta' \Delta \boldsymbol{Z}_{vt} + \Delta\varepsilon_{ivt},$$

$$(2.11)\quad \Delta Y_{iv} = \mu + \delta_{32}\, IAR4D_v + \varphi'(\mathrm{IARD4D}_v \times \mathrm{F}_{it}^{k}) + \delta_2\, Control_v + \beta'\, \Delta \boldsymbol{X}_{it} + \theta' \Delta \boldsymbol{Z}_{vt} + \Delta\varepsilon_{ivt}$$

where $\mathrm{IARD4D}_v$ is a dummy variable equals to 1 for intervention/IAR4D villages and F_{it} is a vector of characteristics (a relevant subset of $\boldsymbol{X}_{i1}$, see below). Parameters associated with the relevant interaction term, φ, reveal whether impact varies with different characteristics (note that φ from (2.10) and (2.11) are equivalent). Parameters δ_{31} and δ_{32} indicate average treatment effects relative to control and conventional villages, as before.

We interact 4 groups of variables with $IARD4D_v$, denoted by superscript k. Three groups are candidates for heterogeneous impact: (*i*) education (*edu_secondary* and *edu_univers*), (*ii*) agricultural experience (*duration*), and (*iii*) access to finance (*borrowed_formal* and *borrowed_informal*). The fourth variable for interacting captures the baseline survey time (*Surv_time*). This interaction term has a different interpretation, and allows us to tentatively explore whether the length of the intervention matters. By extension, this may be informative regarding the potential bias introduced by the fact that conventional villages have benefitted from intervention for a longer time than the IAR4D villages. If the estimate of the coefficient interaction term is jointly significant together with the estimated coefficient for *Surv_time* then the impact of intervention varies with the intervention length.

2.6 Estimation results for poverty indicators

We now turn to the regression results. In Table 2.5 we report average treatment effects of the IAR4D approach in terms of poverty. We report regression outcomes for the DD and FD model. For each model, the left column provides the estimated impact on control villages, and the right column reports differences between IAR4D and conventional extension. When estimating the models we included a full vector of control variables (see Table 2.3), but do not report these coefficients to economize on space.[18]

2.6.1 Intention to Treat Effects

We believe Table 2.5 contains the most important result of this paper. We reach to nuanced set of results. The IAR4D intervention successfully reduced poverty, and is more effective than conventional extension efforts in reducing poverty. Both the DD and FD models indicate that, compared to the control group of "control villages," the number of people below the poverty line has fallen by some 17% on average. Comparing IAR4D and conventional extension approaches produces a slightly smaller impact (approximately 14% fewer poor people), suggesting that the conventional extension strategy hardly outperforms doing nothing. These are striking results, in light of the fact that the IAR4D approach has been implemented for just 2 years, so that we are only picking up short-term effects.

However, the negative signs for the food consumption indicator in row 2 provide do not support the above conclusion. Note that the FCS coefficients are not statistically significant from zero. This could indicate various possibilities. Perhaps the poor prefer to spend part of their extra income on other items than food. Or, alternatively, perhaps extra expenditures on food do not translate into extra calories (but in better-tasting food, say, as argued by Banerjee & Duflo 2011). Subsequent results also suggest considerable heterogeneity in terms of food consumption at the IP level.

[18] Due to missing observations for poverty indicators and control variables, the number of observations reported in Table 4 is lower than documented in Table 1. To test whether missing observations bias our results, we also estimated parsimonious models without control variables and with limited sets of control variables (varying sample size). We conclude our results are robust. To economize on space we do not report those estimates, and they are available upon request.

Table 2.5: Estimated impacts of intervention on poverty and food consumption

	DD		FD	
	IAR4D - Control	*IAR4D – Conventional*	*IAR4D – Control*	*IAR4D – Conventional*
Headcount Ratio	-18.26***	-12.96*	-17.13**	-14.25*
	(6.468)	(6.948)	(7.582)	(8.131)
	[N=402]		[N=163]	
FCS	-1.568	-1.4440.328	-1.195	-2.380
	(1.876)	(1.667)	(1.656)	(1.566))
	[N=3339]		[N=1119]	

Note: In all regression models, the controls listed in Table 2.2 are included (details available on request). Country fixed effects are only controlled for DD models. Robust standard errors are in parenthesis, * $p<0.1$, ** $p<0.05$, *** $p<0.01$. The number of observations is reported in square brackets.

As mentioned above, these estimates may over- or underestimate the effectiveness of innovation platforms. Note that, if there are diminishing (increasing) returns to intervention, then the estimated 14% difference between IAR4D and conventional extension efforts according to the DD and FD model is an overestimate (underestimate) of the true gap in effectiveness over the two-year study period. Regardless, since the headcount ratio in the IAR4D villages was greater than in the conventional villages at the time of the baseline survey (see Table 2.4), it appears as if the IAR4D villages have "caught up."

2.6.2 Heterogeneity across innovation platforms

In Table 2.6 we examine whether there are differences, in terms of impact on the incidence of poverty, across innovation platforms. We provide estimates for θ_{1ip} and θ_{2ip} from (2.8) and (2.9), respectively, for each IP separately. For any IP, the first row corresponds to the impact of IAR4D on the food consumption index and the number of poor people. The second row shows how this estimated impact compares to the impact of conventional extension efforts.

Table 2.6: Poverty impacts at the level of individual IPs

IP name	Country	Estimated coefficients	Dependent Variables FCS	Headcount ratio
Kayonza	Uganda	Θ_{11}	-7.877***	_[19]
		Θ_{21}	-8.880***	
Bubare	Uganda	Θ_{12}	-3.258	-6.087
		Θ_{22}	-2.255	-3.417
Bufundi	Uganda	Θ_{13}	-1.523	- 44.73***
		Θ_{23}	-0.520	-42.06**
Chahi	Uganda	Θ_{14}	-1.929	-30.21**
		Θ_{24}	-0.926	-27.54*
Gataraga	Rwanda	Θ_{15}	6.165**	-20.51
		Θ_{25}	5.162***	-17.85
Remera	Remera	Θ_{16}	-0.433	9.299
		Θ_{26}	0.570	11.97
Rwerere	Rwanda	Θ_{17}	8.912***	-9.552
		Θ_{27}	7.909***	-6.883
Mudende	Rwanda	Θ_{18}	-6.756***	-38.35***
		Θ_{28}	-7.759***	-35.68**
Kituva	DRC	Θ_{19}	-12.09***	-29.13**
		Θ_{29}	-13.09***	-26.46*
Bweremana	DRC	Θ_{110}	-13.20***	8.425
		Θ_{210}	-14.20***	11.09
Rubare	DRC	Θ_{111}	-7.564***	39.21***
		Θ_{211}	-8.567***	41.88***
Rumangabo	DRC	Θ_{112}	-6.501**	11.59
		Θ_{212}	-7.504***	14.25

Note: In all regression models, the controls listed in Table 2.2 except country dummies are included (details available on request). Robust standard errors are in parenthesis, * p<0.1, ** p<0.05, *** p<0.01. The number of observations is reported in square brackets.

The results suggest considerable heterogeneity across IPs. Indeed, there are (*i*) successful IPs where poverty went down (Bufundi, Chahi, Mudende, and Kituva), (*ii*) IPs where poverty appears unaffected, but also (*iii*) IPs where poverty has increased after the implementation of IPs (Rubare). Hence, average treatment effects mask large differences across platforms. Similar heterogeneity exists for our food consumption measure. It is interesting to note that the most successful IPs are the ones with high poverty rates at the baseline, suggesting a catching up process. It is also interesting to note that successful platforms in terms of poverty reduction are scattered across the study region, and not confined to one or two wards or countries with specific characteristics: Bufindi and Chahi

[19] Not available, because baseline headcount ratio data from Kayonza IP are missing.

are located in different districts in Uganda, Mudende is in Rwanda, and Kituva is in the DRC. Hence, the results are not driven by cultural and institutional factors limited to a specific locality. However, and supporting the view that the impact of IPs varies with local conditions, not all poor IPs have above-average growth. For example, Rubare and Rumangabo are poor but not successful. Average poverty rates at the baseline were 57 and 66%, respectively, and poverty rates went up after the intervention.

Note also that the poverty and food consumption scores do not go hand-in-hand for several IPs. For Bufindi, Chahi, Kituva and Mudende, our data suggest a (dramatic) decrease in poverty rates that is not accompanied by an increase in food security scores. This is a puzzling result—perhaps reminiscent of results reported for India by Deaton and Dreze (2009). As mentioned above, it may reflect a near zero income elasticity for the food items included in the FCS measure, but in light of the low baseline score this may not be plausible. Other candidate explanations exist. The estimated poverty impacts may be mismeasured. Recall our poverty data are based on focus group discussions, so they may be imprecise or open to manipulation. Alternatively, perhaps the poverty impact is actually less dramatic than it appears – if the platform translates into a small income gain for a large number of people just below the poverty line, then the headcount ratio falls a lot without affecting consumption patterns of affected households a lot. In other words, a dramatic reduction in the poverty headcount should not be confused with a dramatic increase in income.

There is evidence regarding the country level correlation at the impact of IPs on FCS. We observe statistically negative coefficient for all IPs from DRC although there is heterogeneity within Rwanda and Uganda. Do different regional trends explain the decrease in FCS in the IPs from DRC? To check whether regional trends explains the result we estimate (2.7) for only DRC and find that program did not improve FCS but there is a regional trend biasing the food consumption score negatively.

Of course we are interested in exploring the determinants of IP performance. However, we lack the data to analyse this in any level of detail (we have only 12 observations at the IP level), and believe this question is best addressed at the programme level—pulling together data from the three sites (36 IPs in total). A look at our data, however, suggests IP performance may vary with certain key baseline community characteristics.[20] For example, IP performance varies with a few proxies of social capital. We find robust (partial) correlations between IP success and whether community members make voluntary financial contributions to support community activities, or to remedy communal problems. Hence, pre-existing levels of social capital may be a factor explaining the success or failure of IPs.

While determining the exact mechanism linking innovations to poverty reduction is beyond the scope of the current paper, we emphasize this is an important area for follow-up work. Both the selection of innovations as well as the impact of adoption of specific innovations appears to be context-specific.

2.6.3 Heterogeneity across households

Next we examine whether the impact of IAR4D is conditional on household characteristics—is a subset of villagers able to reap the benefits (if any), while others cannot? In Table 2.7 we provide estimation results for models (2.10-1.11). The two top rows for each group k give estimated values for δ_{31} and δ_{32}, respectively. The other rows present estimates of φ. It is clear that there is no evidence of heterogeneous impact. The impact of IAR4D does not vary with household agricultural experience, access to finance, or education. That is, IAR4D benefits, if any, are shared within the community.

The only interaction term to enter significantly in Table 2.7 measures heterogeneity in time — this interaction term is the product of the IAR4D intervention and the survey time dummy (significant at the 10% level). The interaction term suggests that IPs that have been in existence for two years outperform IPs that have been in existence for only 1 year. All successful IPs started in 2008 (but not all IPs starting in 2008 were successful). Specifically, the more established IPs have on average a reduction in poverty of 20% and the immature IPs see the poverty rate go up by 5%.

[20] To circumvent reverse causality concerns we use pre-IP intervention baseline measures of community characteristics in this analysis.

The latter result, however, should be taken with a pinch of salt, because the nature of our poverty data may not permit strong statements about tiny (short-term) effects. Nevertheless, we speculate that any negative start-up effects may capture the investment component of building an IP – there are significant short-term (opportunity) costs and medium-term benefits will only materialize after the IP is functioning. Such non-linearities in the response to intervention effort may imply that we underestimate the impact of IAR4D relative to the conventional policy (where intervention started earlier, so that initial investment costs have been borne before the experiment started).

Table 2.7: Heterogeneous treatment effects

	Dependent variables	
Dependent variables:	FCS	Poverty
Estimated Impact		
IAR4D – Control	-0.998	-28.61
IAR4D – Conventional	0.109	-25.88
IAR4D × Duration	0.101	0.492
IAR4D – Control	-0.151	-27.93**
IAR4D – Conventional	0.952	-24.45**
IAR4D × edu_secondary	3.675**	38.98
IAR4D × edu_univer	0.944	-14.69
IAR4D – Control	3.115	-28.37
IAR4D – Conventional	4.207	-25.86
IAR4D × borrow_formal	-9.165*	69.27
IAR4D × borrow_informal	-2.084	2.272
IAR4D – Control	1.180	-20.33**
IAR4D – Conventional	2.273	-18.02**
IAR4D × survtime	0.199	25.70*

Note: In all regression models, the controls listed in Table 2.2 except country dummies are included (details available on request). Robust standard errors are in parenthesis, * p<0.1, ** p<0.05, *** p<0.01.

2.7 Probing the mechanism: Platforms and innovation

How does IAR4D lower poverty? As a first stab regress the adoption of our innovation indicators on the IP treatment by using linear probability models (i.e., we estimate (2.6) and (2.7) using innovation variables as dependent variables). We ask whether there are significant differences in terms of adoption between the three types of villages. Estimation results are given in Tables 2.8 and 2.9. We only report (differences in) coefficients of interest, but again these models were estimated with a full vector of controls.[21]

The innovation impact, as summarized in Tables 2.8 and 2.9, is less pronounced than the poverty impact summarized in Table 2.5. On average, IAR4D does not have a robust and significant positive impact on the adopting of these innovations. Instead, the DD and FD models suggest IAR4D is associated with the dis-adoption of certain technologies, such as the probability of using animal manure or the use of certain post-harvest technologies (drying). A similar picture emerges with respect to other innovation proxies, related with regulation, marketing strategies and village resources. According to Table 2.9, IAR4D does not have a significant positive impact on the average probability of adoption.

However, these results should not be surprising, and do not discredit the innovation systems hypothesis. For instance, Pamuk et al. (2014b) analyse the impact of IAR4D on technology adoption for all PLSs (i.e., not just the Lake Kivu PLS analysed in this paper), and show that priorities vary across IPs. Indeed, the lack of significant *average* treatment effects in terms of adoption of specific innovations is the natural outcome given that priority setting is decentralized. Since each IP decides on its own priorities, reflecting local preferences, opportunities and constraints, each IP should settle on its own "innovations" and average treatment effects are difficult to detect.

For this reason, we also tested for heterogeneity in terms of the types of innovations that are adopted. This implies estimating (2.10) and (2.11) and using our innovation indicators as dependent variables. Detailed regression results are many, and are not shown here to economize on space (but they are available on request). Summarizing the main insights, and consistent with results by Pamuk et al. (2014b), adoption priorities vary from one IP to another. This is true both for the technical as well as the governance-related innovations. For example, in Bubare conservation farming has significantly increased while plant spacing and organic pesticide usage decreased. In Bweremana mulching and

[21] Our analysis regarding technology adoption is limited in the sense that we do observe the impact of the intervention on simultaneous adoption of multiple technologies as discussed by Dorfman (1996).

row planting usage increased, and manure use decreased. Similarly, in some IPs market integration has gone up, while in others it went down. There does not appear to be a systematic pattern in terms of innovations adopted by IPs.

Table 2.8: Estimated impact of Intervention on agricultural technologies

	DD		FD	
Dependent Variables	$Interv - Control$ $(-\delta_1)$	$Interv - Conv$ $(-\delta_2)$	$Interv - Control$ $(-\delta_1)$	$Interv - Conv$ $(-\delta_2)$
Mulching	-0.0528	0.00842	-0.0310	-0.00697
	(0.0472)	(0.0465)	(0.0476)	(0.0461)
Trenches/terraces	-0.0186	0.0459	0.00162	0.0740*
	(0.0443)	(0.0446)	(0.0444)	(0.0431)
Water harvesting	-0.0107	-0.0280	-0.0209	-0.0416
	(0.0400)	(0.0375)	(0.0461)	(0.0421)
Irrigation	-0.0229	-0.0163	-0.0242	-0.0162
	(0.0284)	(0.0286)	(0.0306)	(0.0300)
Conservation farming	-0.00353	-0.0169	-0.0195	-0.00684
	(0.0537)	(0.0478)	(0.0622)	(0.0523)
Animal manure	-0.103**	-0.0778*	-0.117**	-0.0831*
	(0.0472)	(0.0426)	(0.0523)	(0.0470)
Cover crops	0.0195	0.00778	-0.00680	-0.00445
	(0.0432)	(0.0428)	(0.0474)	(0.0472)
Crop rotation	-0.0474	0.0361	-0.0462	0.0388
	(0.0430)	(0.0385)	(0.0444)	(0.0407)
Inter cropping	-0.0245	-0.0615	-0.0161	-0.0504
	(0.0532)	(0.0492)	(0.0567)	(0.0510)
Rhizobiainoculation	-0.0150	-0.0113	-0.0254	0.000283
	(0.0155)	(0.0150)	(0.0173)	(0.0150)
Chemical fertilizer	0.00326	0.00767	-0.00561	0.0189
	(0.0298)	(0.0301)	(0.0305)	(0.0318)
Row planting	0.0348	0.0208	0.0562	0.0385
	(0.0458)	(0.0406)	(0.0488)	(0.0443)
Plant spacing	-0.0281	-0.0160	-0.0166	0.00418
	(0.0540)	(0.0529)	(0.0580)	(0.0546)
Organic pesticide	-0.0355	0.00329	-0.0162	0.0143
	(0.0322)	(0.0334)	(0.0325)	(0.0339)
Inorganic pesticide	0.0264	0.0177	0.0383	0.0172
	(0.0352)	(0.0387)	(0.0365)	(0.0416)
Drying	-0.108**	-0.0790	-0.0895*	-0.0718
	(0.0537)	(0.0483)	(0.0533)	(0.0478)
Threshing/shelling equipment	-0.0110	0.0559	0.00296	0.0802
	(0.0540)	(0.0500)	(0.0528)	(0.0504)
Improved storage facilities	-0.00540	-0.00798	0.0167	0.0131
	(0.0486)	(0.0423)	(0.0497)	(0.0431)
Pest control	0.0683	0.0209	0.0731	0.0362
	(0.0603)	(0.0546)	(0.0646)	(0.0594)
Grading	-0.0225	-0.00513	-0.0142	-0.00868
	(0.0611)	(0.0588)	(0.0641)	(0.0615)

Note: In all regression models, the controls listed in Table 2.2 except country dummies are included (details available on request). Robust standard errors are in parenthesis, * p<0.1, ** p<0.05, *** p<0.01.

Table 2.9: Estimated impact of intervention on the probability of land regulations and marketing strategies and village resources

Dependent Variables	DD $Interv - Control$ $(-\delta_1)$	 $Interv - Conv$ $(-\delta_2)$	FD $Interv - Control$ $(-\delta_1)$	 $Interv - Conv$ $(-\delta_2)$
Land regulations				
nrmbylaws	-0.131	-0.107	0.0108	-0.000929
	(0.0889)	(0.0874)	(0.0708)	(0.0712)
landlaws	-0.0959	-0.127	0.0511	-0.0213
	(0.0869)	(0.0933)	(0.0796)	(0.0798)
Marketing strategies				
notsold	-0.0674	-0.0585	-0.0575	-0.0685
	(0.0602)	(0.0601)	(0.0612)	(0.0629)
consumers	0.0384	0.0611	-0.00995	0.0547
	(0.0339)	(0.0378)	(0.0374)	(0.0380)
middleman	-0.0274	-0.00650	-0.0389	-0.0160
	(0.0351)	(0.0350)	(0.0365)	(0.0362)
on road side	-0.0205	-0.00927	-0.0102	-0.0279
	(0.0297)	(0.0288)	(0.0332)	(0.0301)
local market	-0.00508	0.00334	-0.0104	0.0188
	(0.0548)	(0.0517)	(0.0571)	(0.0544)
district town	0.00468	-0.0125	0.00439	-0.0121
	(0.0203)	(0.0203)	(0.0217)	(0.0224)
distant market	-0.0477*	-0.0366	-0.0449	-0.0274
	(0.0252)	(0.0267)	(0.0293)	(0.0313)
sold	-0.0376	-0.0471	-0.0640*	-0.0567
	(0.0374)	(0.0356)	(0.0377)	(0.0354)
Village resources				
wells	0.0422	0.0244	0.0393	0.0160
	(0.0881)	(0.0843)	(0.0962)	(0.0884)
veterinary	-0.00523	-0.0640	-0.0285	-0.0969
	(0.0749)	(0.0656)	(0.0764)	(0.0690)
woodlots	0.0724	-0.0374	0.108	-0.0371
	(0.108)	(0.109)	(0.107)	(0.110)
waterbody	-0.0435	-0.00289	-0.0683	-0.0776
	(0.115)	(0.115)	(0.125)	(0.131)
wateringpoint	-0.232**	-0.131	-0.232**	-0.138
	(0.0901)	(0.0863)	(0.0945)	(0.0888)
agriresearch	0.0928	0.0211	0.0203	-0.0471
	(0.0594)	(0.0598)	(0.0615)	(0.0595)

Note: Estimates from the regressions indicated in the text are given. In all regression, controls listed in Table 2.2 except country dummies are used during the estimation. Robust standard errors are in parenthesis, * p<0.1, ** p<0.05, *** p<0.01

We can focus on the choices made by the four IPs most successful from a poverty alleviation perspective: Bufindi, Chahi, Mudende, and Kituva. For these IPs, adopted innovations appear predominantly institutional in nature. Given the short time frame after the intervention (two years), this is perhaps not unexpected. Insofar as it is easier to change institutions and governance arrangements than to pioneer with technical innovations and upscale their use, we might expect institutional reform to have impact relatively quickly. Key innovations in successful IPs are enhanced market access (Chahi, Kituva), adoption of new land regulations (Bufindi), and improved access to village resources (Mudende). Occasionally these governance innovations were complemented with technical innovations (e.g. post-harvest pest control in Chahi, and mulching, irrigation, inter cropping, row planting, organic pest and post-harvest management in Kituva).

While determining the exact mechanism linking innovations to poverty reduction is beyond the scope of the current paper, we emphasize this is an important area for follow-up work. Both the selection of innovations as well as the impact of adoption of specific innovations appears to be context-specific. For example, while successful IPs have focused on developing marketing strategies, changing access to land and the application of specific technologies, our dataset also provides counter examples to these success stories. Bweremana adopted the same technologies as Kituva, but in Bweremana this did not result in a lower poverty rate. The match between local conditions and innovations determines the success of an IP, but this will have to be explored more carefully (perhaps using qualitative methods).

2.8 Conclusions and discussion

Conventional extension efforts have by and large failed to generate the widespread adoption of innovations that are considered necessary to advance the agricultural development agenda. In response, the search is on for alternative mechanisms that foster innovation, adoption and diffusion, and alleviate poverty. We report short-term evidence on the effectiveness of one such initiative—decentralized and participatory innovation systems. As part of a large experiment, so-called innovation platforms have been introduced in a sample of selected villages. The performance of these villages, in terms of poverty reduction, is compared to the performance of two different counterfactual groups; control villages and villages benefiting from traditional extension approaches. Even though the period between baseline and follow-up survey was short, extending to not more than 2 years, surprisingly we are able to document some impact of innovation platforms on poverty rates.

Our main conclusions are fourfold. First, we reach to mixed results concerning the average treatment effects of the innovation system intervention. On average, innovation platforms reduce poverty according to our focus group measure of poverty, but the platforms did not increase the food consumption. Second, the participatory approach appears more effective than traditional extension efforts in alleviating poverty. Third, the impact of the intervention according to our poverty measure is not limited to local elites. Instead, the impact does not vary (much) with household characteristics. Fourth and reflecting the decentralized nature of the innovation systems approach, different platforms prioritize different types of innovations. We speculate this diversity reflects variation in local opportunities and constraints. Next steps in our research agenda on innovation systems are (*i*) to analyze the mechanism linking IPs to poverty reduction (the adoption of specific innovations – see Chapter 3, which documents that the participatory model promotes the adoption of crop management innovations, but find no significant effects for other types of innovation), and (*ii*) to systematically compare the costs and benefits of IAR4D and alternative approaches to innovation and diffusion at IP level - yet we may argue that the program may be inefficient since we do not observe a robust negative impact on poverty and the program involves a cost.[22]

Two caveats should be mentioned. First, we did not implement an RCT where villages are randomly assigned to either the IAR4D treatment, or to one of the two counterfactual groups. We aim to control for potential selection bias by estimating difference-in-difference models and panel models, but cannot completely rule out that some estimation bias eventuates due to unobservable and time-varying factors. Second, we obtain the most interesting results for our poverty data, which are not based on detailed household measurements but reflect the outcome of focus group discussions of local village leaders. The reduction in poverty for some villages is dramatic, and is not consistently matched by improvements in our measure of food consumption. This could point to an interesting empirical puzzle, inviting follow-up analysis, or could point to mismeasurement of local poverty rates. Perhaps the focus group approach to data collection did not produce

[22] We cannot compare the efficiency of the conventional approach and IAR4D, as we do not have access to cost data for the conventional projects..

precise measures of local poverty, or perhaps it resulted in biased assessments. For example, the enhanced social interaction associated with the IP treatment could affect the outcomes of the poverty assessment (as both are inherently social processes). Alternatively, "local leaders" may have strategic reasons to misrepresent local poverty rates. However, it is not evident (to us) whether they should over- or under-represent such rates. If they do not want to disappoint the researchers, village leaders in IAR4D villages may under-represent poverty rates during the midline. But if the aim is to attract additional funding and projects, then perhaps poverty rates are over-estimated (sending a signal of urgency). Hence, and also in light of the observation that poverty rates were not balanced during the baseline, we emphasize the importance of efforts to verify our findings in other contexts, perhaps using alternative proxies for poverty and (food) consumption.[23]

Notwithstanding these important caveats, the evidence suggests that decentralized innovation systems, based on participation of a wide range of stakeholders, may represent a promising vehicle to promote agricultural development. It provides tentative support for the recent transition to "new demand-led approaches to extension" identified by the World Bank (World Bank, 2007). However, other considerations are relevant and should be mentioned here. First, while the innovation platform approach on average generates positive impacts, there are also platforms that apparently have failed to generate any short-term benefits. It is clearly a first order priority to analyse and explain the variation in performance. Does short-term success depend on the nature of the platform implementation process—anecdotal evidence suggests there has been variation in the way these platforms have been initiated and governed—or does it depend on characteristics of the affected communities (e.g. pre-existing levels of social capital)? Or have farmers adapted new technologies without really understanding them technologies because they have felt that this has been expected from them and not been committed to the project – so is there a Hawthorne bias? Or is it simply true that in some platforms a consensus was reached to focus on innovations that pay off in the longer term, so that lack of a short-term

[23] Note that our results may also be explained by non-random selection of IP sites for additional interventions. However, there is no evidence of "other interventions" systematically benefitting the villages selected for IAR4D. We have not kept track of all "other interventions" in comparison areas, so we cannot rule out that another intervention targeted non-intervention sites and had *negative* impacts on poverty alleviation there (explaining the positive estimated impacts in our study). However, we believe this to be unlikely.

effect is not indicative of platform failure at all? Follow-up research is needed to analyse this issue. Our preliminary analysis of the data suggests that the nature of the innovations selected and adopted varies across IPs—as is to be expected with a decentralized innovation approach.

Second, decentralizing priority setting in the domain of innovation involves a trade-off. While decentralized approaches, such as IAR4D, allow tapping into pools of local knowledge and understanding, it might imply foregoing potential economies of scale in R&D. A particularly bad outcome—not one that is consistent with our data—would be where many platforms are inventing the same wheel. Moreover, a decentralized approach might induce a focus on bottlenecks that can be addressed locally. The macro-perspective, involving large-scale investments in physical infrastructure or national, sectoral or trade policies, might be overlooked. It appears important to give more space and attention to the use of the decentralized approach to innovation, while engaging policy makers of the “right level” as well. The challenge will be to find the right balance between centralized and decentralized efforts to get African agriculture going.

Chapter 3

Do decentralized innovation systems promote agricultural technology adoption? Experimental evidence from Africa[ϒ]

3.1 Introduction

Agricultural intensification and development is widely seen as a pre-condition for sustainable pro-poor growth in Africa (WDR 2007, Haggblade et al. 2007, Ligon and Sadoulet 2007, Christiaensen et al. 2010). An important component of many agricultural development strategies is the promotion of (the adoption of) innovations. Slow rates of technology adoption in African smallholder farming are a key factor explaining stagnating agricultural yields across the continent. Given that utilizing these technologies appears to be profitable in developing countries on average, rational profit maximizing farmers should have adopted these technologies theoretically. So, what are the reasons of imperfect? Shortly, recent studies provide four important theoretical explanations for this, which have been supported by empirical evidences, for this puzzle: (1) the farmers may have behavioral biases (risk aversion and present bias) distorting their investment decisions and leading to underinvestment and (2) may not be aware of the technology or do not know how to use it; (3) the returns to the technologies may be heterogeneous among farmers and very low for the non-adopters due to the context (infrastructure and trading opportunities) and characteristics (demographic factors and access to credit); of farming households. Moreover, (4) there may be factors associated with the technologies themselves which

[ϒ] This Chapter is based on following research paper: Pamuk, H., Bulte, E., & Adekunle, A. A. (2014b). Do decentralized innovation systems promote agricultural technology adoption? Experimental evidence from Africa. *Food Policy*. 44, 227-236.

make them less suitable for smallholders (for example, they may imply demands for complementary inputs that are not always available). Hence, it may not be optimal to adopt various new technologies."

Another factor responsible for lagging adoption rates is the design of most extension programs, which by and large is based on the perspective that the diffusion of innovations resembles a 'linear process.' According to this perspective, key agricultural innovations are created by specialists (researchers), distributed by other specialists (extension workers), and adopted by producers (Leeuwis and van de Ban 2004, Knickel et al. 2009). Such linear diffusion processes have been challenged by recent insights emphasizing social learning within (non-linear) networks (e.g., Bandiera and Rasul 2006, Conley and Udry 2009), and by academic work that identifies heterogeneity among smallholders so that 'blanket recommendations' are unlikely to be relevant for large swaths of the farming population (Duflo et al. 2008, Suri 2011). These issues, combined with problems due to insufficient public funding and perverse incentive effects, have prompted policy makers and academics to probe alternative innovation and diffusion modalities. For example, capacity building and farmer empowerment have gained in importance in recent years, at the expense of more prescriptive approaches (WDR 2007).

One recent attempt to revolutionize innovation and diffusion processes in rural Africa is the so-called Sub-Sahara African Challenge Program (SSA-CP; see below). Unlike conventional, top-down extension approaches, the SSA-CP articulates an "innovation system" perspective, integrating and building on knowledge and preferences from stakeholders across the production and distribution chain. Innovation systems are intended to be "participatory," and seek to engage not only research experts but also representatives from appropriate government bodies as well as producers, intermediaries, customers, and financial organizations. These stakeholders are brought together in so-called local "innovation platforms," enabling bottom-up searches for solutions to local bottlenecks. A priori it is not evident whether the traditional, centralized model or the participatory model represents the most efficient and effective vehicle to promote agricultural development. While economies of scale in innovation and transfer argue in favor of standardized, centralized approaches, the decentralized approach allows tapping into local knowledge about constraints, possibilities and priorities which may enhance local demand for innovations on offer.

In a companion paper we have analyzed and compared the poverty impacts of traditional extension approaches and the decentralized innovation system approach (Pamuk et al. 2014a). Based on experimental data collected in selected villages in the DRC, Uganda and Rwanda, we found that the decentralized innovation systems approach outperforms the traditional linear extension model in terms of poverty alleviation. However, we also documented considerable heterogeneity in performance across localities, and were silent on the mechanism linking innovation systems to poverty impacts.

The main objective of this paper is to identify the impact of decentralized innovation systems on the adaption of different agricultural technologies, a potential mechanism linking innovation systems to poverty impacts. In addition, we explore whether the benefits of the "innovation system" approach are widely shared within rural communities, or whether local elites are able to capture most of them (i.e., we probe the issue of intra-platform heterogeneity). As before, we will base our analysis on experimental data collected during implementation of the SSA-CP (see below). However, unlike the earlier analysis in Chapter 2 we will not focus on one specific learning site – the poverty analysis was based on data from Central Africa only. Instead, we pull together data across all program sites in West, Central and Southern Africa. In addition, we will move beyond village-level variables (i.e. poverty rates), and focus on household-level adoption and disadoption data.

Our main results support and complement the findings in Pamuk et al. (2014a). Specifically, we identify one rather robust impact of innovation platforms on farm management across project sites – potentially a channel via which poverty rates are reduced. In addition, while we document heterogeneity across platforms, reflecting that decentralized solutions reflect diversity in local priorities and challenges, we find no evidence of elite capture, or intra-village differences in impact. Finally, we are not able to document any impact for a subsample of the platforms, and provide tentative evidence that the impact of the innovation systems approach varies predictably according to local initial conditions.

This paper is organized as follows. In section 3.2 we briefly summarize key elements of the Sub Sahara African Challenge Program, and the nature of its main intervention—the creation of innovation platforms in selected villages. Section 3.3 summarizes our data and identification strategy. In section 3.4 we present the results, paying most attention to the household-level impacts of innovation platforms in terms of farm management and marketing strategies. Section 3.5 concludes.

3.2 Program description: The SSA-CP

In 2004 the Challenge Program (SSA CP) introduced a new approach to promoting innovation and diffusion of innovations in African agriculture. This so-called Integrated Agricultural Research for Development (IAR4D) approach was based on an innovation systems perspective, and created coalitions of stakeholders to identify and address local bottlenecks to agricultural development. Through this approach, the program aims to promote agricultural innovations by utilizing indigenous knowledge of the farmers through a participatory framework and interaction between different stakeholders.

A central concept in this approach is the so-called innovation platform (IP), which are decentralized local innovations systems. IPs are vehicles to bring together stakeholders. Each IP serves a group of villages, and theoretically chooses representatives from different stakeholders via a participatory process. These representatives of farmers' associations, traders, researchers, extension workers, NGOs, and government policy makers regularly meet at these platforms, articulate their views, and negotiate joint strategies for action. In light of diversity in challenges across localities, one would expect different IPs to prioritize different problems and to formulate different strategies for action such as research and adoption of new agricultural technologies, crops, introduction of new natural resource management practices, institutions —IPs should be a springboard for participatory and bottom up processes. In addition, the IPs should engage the broader communities within which they are operational by raising awareness and the spreading of information via assigned IP members (FARA 2008).[24]

The Forum for Agricultural Research in Africa (FARA) coordinates the implementation of the SSA-CP. To provide "proof of concept," the IAR4D program was rolled out as a large experiment, whereby some communities received IPs (treatment communities) and others did not (control communities).[25] A range of livelihood variables was tracked in both the treatment and control communities via two survey waves. The current study is based on baseline data collected in 2008 and midline data collected in 2010-2011. This means we can only pick up short-term effects, and can only assess the impact of early maturing platforms. An end-line survey is scheduled for late 2013, enabling additional analysis probing the robustness and sustainability of the preliminary results presented here. As mentioned, a comparison of the dynamics of poverty rates for a subsample of the communities monitored over the period between baseline and midline (2008-2010) suggests that IAR4D managed to reduce local poverty (Pamuk et al. 2014a).

To guaranty external validity of the lessons learned, IPs were introduced in three African sub-regions, or "project learning sites" (PLS): (*i*) "Lake Kivu (LK)" in Eastern and Central Africa, (*ii*) "Kano-Katsina-Maradi (KKM)" in West Africa, and (*iii*) "Zimbabwe-Malawi-Mozambique (ZMM)" in Southern Africa. The enormous variation across project learning sites, in terms of both geophysical and socioeconomic variables, enables verification whether any impact effects are robust to changes in contextual factors, or not. Per project learning site, multiple task forces were created to supervise the implementation and data collection process. The identity of the implementing partner at the task force level varied from one locality to the next, depending on local and relevant expertise, and sufficient presence in the region.

[24] Please see section 2.3 for details of the program.

[25] The SSA-CP has two types of control groups: (i) so-called 'clean villages' where heretofore no serious extension efforts (by either the state or NGOs) has been lacking and (ii) so-called 'traditional extension villages,' which in the past have been selected for such treatment. The IAR4D villages were drawn from the pool of clean villages (see main text, below), so to attenuate concerns about selection effects, which could plague impact assessments of IAR4D vis-à-vis traditional extension villages, the pool of clean villages is used as the sampling frame in this study and we only compare the performance of the IAR4D treatment relative to the control group of clean villages.

To promote internal validity, as mentioned, the implementation stage was organized as an experiment with exogenous selection of villages into the IAR4D treatment. The details of the sampling frame were slightly different across PLSs. Specifically, in West and Southern Africa the intervention was implemented as a conventional RCT. A sampling frame was constructed that included so called "clean villages" in the study region or villages relatively untouched by either conventional extension efforts or diffusion projects of non-governmental organisations (NGOs). From this sampling frame, a subsample of villages was randomly drawn to receive the treatment, and a subsample of villages from the rest of the sampling frame was randomly selected to serve as control. Finally, a random sub-sample of villagers (households) was drawn from treatment and control villages and subsequently included in the waves of surveying.

In the Lake Kivu region, capturing parts of Uganda, Rwanda and the DRC, a slightly different approach was followed. To mitigate potential spill-over effects (benefits from treatment – ideas, innovations – affecting well-being of households in control villages), randomisation took place at a higher administrative level than the village level. That is, the sample frame consisted of *wards* (named *sub-counties* in Uganda, *secteurs* in Rwanda, and *groupements* in the DRC). Next, 4 wards per country were randomly selected to receive the treatment, and 4 other wards were randomly selected to act as control wards. From these two sub-samples, random subsamples of treatment and control villages were drawn. Obviously the gains in terms of reduced spill-over effects must be traded off against the costs of a compromised "balance" across treatment and control villages. Since treatment and control villages are drawn from different populations (i.e., from different wards), there is less reason to assume that baseline values for the variables of interest are identical. This is confirmed in the analysis (see below). To control for any differences in the sampling approach we will consistently use Action Zone fixed effects[26] in the analyses.

[26] Action Zone fixed effects refer to country fixed effects for Lake Kivu and ZMM pilot learning sites, and taskforce fixed effects for KKM. Since in KKM, 3 taskforces were active in two countries (Nigeria and Niger), we chose taskforce fixed effects to capture any geographic unobserved factors.

3.3 Data and identification strategy

Initially, the SSA-CP was designed to include 3 project learning sites, 3 task forces per PLS, and 4 innovation platforms per task force. Hence, in total 36 IPs were created. However, one of the task forces failed to collect baseline data on a key technology adoption variable, and another one failed to collect the end-line data in a timely manner. These two task forces were dropped from our sample. Hence in this Chapter we use data from all PLSs (including data from LK-PLS used in Chapter 2), but some data are missing for some task forces within those PLSs. The remaining sample consists over slightly over 3000 households (slightly over 320 villages), rather equally spread across the treatment and control sample. Details of the sampling frame are summarized in Table 3.1. These data suggest mild attrition, but for most models estimated below we will use samples sizes that are smaller than the numbers reported here as not all questionnaires were filled out completely.[27]

Table 3.1: Sampling frame

Survey	Unit of analyses	Intervention	Control	Total
Baseline	Households	1589	1572	3161
	Villages	159	165	324
Midline	Household	1484	1554	3038
	Villages	156	164	320

[27] We tested whether there are systematic differences between complete and incomplete questionnaires in terms of outcome variables. We regress a dummy variable (equal to 1 if the variable is missing for each technology group) on the midline dummy, IAR4D dummies, and control for action zone fixed effects (discussed in section 3.1). We find that education (+), midline (-),gender (-), and action zone fixed effects enter significantly. However, since the impact of IAR4D does not vary with education and gender of the household (see section 4 for detail), this should not introduce bias in our results. The negative sign of the midline dummy implies that the quality of surveys has increased over time (we see the same trend for all technology groups).

Table 3.2: Definitions of our outcome variables and comparison of average level of outcome variables and households characteristics at IAR4D and control villages in baseline

Variable	Definition	Comparison of outcome and household characteristics in baseline
Outcome variables		$\bar{Y}_{IAR4D} - \bar{Y}_{Control}$
Totsw	Total number of soil and water management technologies adopted (0-6)	0.0515 (0.0864) [2725]
Totsf	Total number of soil and fertility management technologies adopted (0-7)	0.257** (0.103) [3035]
Totcm	Total number of crop management technologies adopted (0-5)	0.0383 (0.126) [2863]
Totph	Total number of post harvest technologies adopted (0-6)	0.0821 (0.134) [2899]
Control variables-Household characteristics		$\bar{X}_{IAR4D} - \bar{X}_{Control}$
Gender	Equals 1 if household head is male, 0 otherwise	-0.00843 (0.0381) [3109]
Age	Age of household head	-1.049 (0.706) [3144]
Education	Equals 1 if household head has over primary education, 0 otherwise	-0.0252 (0.0225) [2815]
Household size	Total number of members of household	-0.380 (0.480) [3132]
Agricultural Experience	Years of agricultural experience of household head	-1.261 (0.851) [3104]

Notes: Robust standard errors clustered at village level in parentheses and numbers of observations are in brackets. *** p<0.01, ** p<0.05, * p<0.1

We introduce our outcome variables and control variables in Table 3.2. All outcome variables are measured at the household level, and capture whether or not the household uses a specific production, management, or storage modality. Variation in the use of specific technologies or modalities over time implies the household in question has adopted or disadopted specific practices. Our identification strategy rests upon the correlation between such adoption measures and exposure to IAR4D. We use four count data measures indicating how many technologies are used for a specific purpose. We distinguish between technologies to promote soil and water management (*totsw*), soil fertility management (*totsf*), crop management (*totcm*), and post-harvest storage (*totph*). Details of these technologies are provided in the Appendix, as are summary statistics of the various control variables. As controls we use years of agricultural experience, age, education and gender of the household head, and the size of the household.

3.3.1 Comparing treatment and control variables at the baseline

Since not all IAR4D and control villages were randomly selected from the sampling frames, we first probe to what extent the experiment produced a balanced sample. To what extent do treatment and control villages have similar values for the variables of interest? Table 3.2 reports differences in outcome variables and household characteristics across the two samples. In spite of the large number of observations and high power of the test, we find that for 8 out of 9 variables there are no significant differences between treatment and control villages. The exception to the rule is soil fertility management – households in intervention villages were slightly more likely to engage in these activities than households in control villages. Since failing to account for such pre-existing differences may produce biased impact estimates, we will not base the empirical analysis on simple comparisons of end-line data. Instead, the core of our analysis rests on differences in difference estimates, which under the assumption of parallel trends should address the absence of perfect balance at the baseline. In addition, we use baseline data to increase the power of our estimations, particularly for the IP level estimations based on relatively few observations (see section 3.4).

3.3.2 IAR4D and adoption

We now outline our identification strategy. We are interested in analysing the impact of IAR4D on the adoption (or disadoption) of specific technologies and trade modalities. We use a differences-in-difference (*diff-in-diff*) methodology that combines baseline and midline data.[28] Specifically, we estimate the following model for outcome variable *Y*, and test the hypothesis: $\beta_1^j \neq 0$:

$$(3.1) \qquad Y^j_{ivt} = \beta^j_0 + \beta^j_1\,(IAR4D_v \times Midline_t) + \beta^j_2\, IAR4D_v + \beta^j_3\, Midline_t + \beta^{j'}_4\, X_{ivt} + \varepsilon^j_{ivt}$$

where superscript *j*, and subscripts *i*, *v* and *t* denote innovation item, household, village and time, respectively. Y^j_{ivt} represents the outcome variable, or the set of variables summarized in Table 3.2. *IAR4D* is a dummy variable, with value 1 if the village received the IAR4D treatment (and value 0 otherwise). *Midline* is another dummy, indicating whether the observation in question was collected at the midline, or not (if so, the variable takes a value of 1). Finally, *X* is a vector of controls and ε is the random error term.

We estimate model (3.1) several times, for different samples and using different estimators. (1) We estimate simple Poisson models for our count data outcome variables respectively, without controls, using the largest sample possible (i.e. an unbalanced sample based on all observations). (2) We re-estimate the same model, but now use a smaller sample (only including these households for which there are no missing observations for any of the control variables). (3) Using the same sample as in (2), we now control for household characteristics. (4) Further decreasing the sample we now focus on those villages for which we have both baseline and midline data (balanced sample). (5) We check the robustness of the results obtained using the previous model by estimating an OLS model. (6) We control for unobserved village characteristics by replacing action zone dummies by village fixed effects. (7) We again decrease the sample to the households for

[28] Our diff-in-diff strategy depends on the assumption that outcome variables for control and IAR4D villages have parallel trends. The randomization produced comparable counterfactual groups having similar baseline characteristics (see section above), so we may expect that the trends in outcome variables would be similar if there was no treatment. We cannot however test this assumption, because of lack of data for those variables from the periods before the intervention started. If the villages have differences in terms of some unobserved characteristics or there are other outside factors affecting only IAR4D or clean villages, our results may be biased. Therefore, we should be cautious while interpreting the results.

which we have baseline and midline data (balanced sample at household level). (8) Finally, we control for unobserved household heterogeneity by replacing village fixed effects by household fixed effects.

3.3.3 Are Innovation Platforms able to deliver what is intended?

Since IPs are supposed to identify and diagnose local problems, there is no a priori reason to suspect that all platforms will prioritize similar sets of innovations or technologies. To test whether platforms are able to target locally relevant bottlenecks, we divide the sample of IPs into subsamples, based on local priorities as defined during early platform meetings, and next look technology adoption in the relevant domain. That is, we again estimate (3.1). But for each outcome variable of interest, say crop management technologies, we now only include households from those IPs that intended to focus on that outcome variable. IP priority setting and active policy areas (focus areas) are obtained from IP level reports, and IPs might set more than one priority in the meetings. Hence, for each dependent variable our subsamples are not mutually exclusive. For each subsample we again test whether $\beta^j_1 \neq 0$. Additionally, if we find that IPs with $\beta^j_1>0$ are the ones that were successful in reducing poverty in Chapter 2, then we can conclude IPs may reduce poverty through this channel.

3.3.4 Heterogeneous treatment effects at the household level

Insofar as IAR4D is able to increase innovation rates or the diffusion of new technologies, are all households able to capitalize on this opportunity? Or does a non-random sub-sample of villagers seize these benefits, possibly accentuating pre-intervention differences in local income, well-being or power? To probe this important issue, we estimate the following model in the same subsample discussed in section 3.3.3 and test whether $\alpha^j_1 \neq 0$:

$$(3.2)\qquad Y^j_{ivt} = \beta^j_0 + \alpha^j_1 (Z_{ivt} \times IAR4D_v \times Midline_t) + \alpha^j_2 (Z_{ivt} \times IAR4D_v) + \alpha^j_3 (Z_{ivt} \times Midline_t) + \beta^j_2 (IAR4D_v \times Midline_t) + \beta^j_3\, IAR4D_v + \beta^j_3\, Midline_t + \beta^{j'}_4 X_{ivt} + \varepsilon^j_{ivt}$$

where Z refers to various candidate household characteristics, such as the level of education, which might affect the household's ability to benefit from IAR4D.

3.3.5 Heterogeneous treatment effects at the platform level

In addition to heterogeneity at the level of participating households, we are also interested in heterogeneity at the level of IPs. Specifically, we explore which baseline variables are associated with successful platforms, or with enhanced adoption of innovations. We thus build on the earlier analysis, identifying the platforms able to raise adoption rates of innovations in priority policy areas (see section 3.3.3). In other words, we assume an IP as successful if on average villagers adapt a prioritized technology in the IP.[29]

We distinguish between two types of conditioning variables. First, the success of IPs may depend on "community factors" such as social capital or resources available at the village (e.g. see Khwaja 2009). We proxy the former using survey-based measures of participation in (and financial contribution for) community activities, trust among villagers, cooperation among people, gift giving, assistance to the local poor, resolution of conflicts and disputes, respect for local norms and bylaws, and gender equality. Proxies for village level resources are the presence or absence of schools, clinics and health centers, places of worship, and centers for social activity, but also productive resources such as boreholes (or wells), village wood lots, all-weather roads passing through the village, water bodies (stream, ponds, rivers), public transport stop, or rural micro-finance bank. It is evident that many of these village level resources are not proper exogenous explanatory variables. In what follows we therefore refrain from making causal statements, and simply use a series of *t*-tests to document correlations or associations (future work could try to instrument for key context factors and try to tease out causal effects). We also re-estimate model (3.1) for those context variables correlated with success, and test our hypothesis for the entire sample.

Second, the success or failure of IPs could be associated with the nature of the implementation strategy. That is, while the philosophy behind innovation platforms is rooted in concepts like participation and bottom-up processes, the extent to which local stakeholders were actually engaged in priority-setting might vary from one platform to the next. We obtain a rough proxy for the degree to which platforms appear to encourage such

[29] These are the IPs for which we find a significant and positive impact of intervention in Table 4

local variety, and again correlate this proxy to our measures of platform success. Our proxy for the extent to which platforms were driven by participatory processes is based on variation in policy priorities across IPs at the task force level.

Assuming that decentralized priority setting translates into some diversity in priority areas, we interpret the lack of such diversity as evidence of some degree of top-down planning. Obviously such arguing might be misleading, as we cannot rule out that decentralized stakeholders converge to the same overarching concern within one taskforce's territory. We therefore interpret these correlations with even more caution than the other empirical results. Nevertheless, and as a first attempt to operationalize this concept, to assess whether top-down platforms are more or less effective than bottom-up ones, we again estimate model (1), but now divide the sample based on this indicator for top-down planning.

Specifically, we characterize an IP as 'top-down' if it belongs to a taskforce in which all IPs focus on the same bottleneck For example, in Sudan Savannah all IPs focus on soil and fertility management and on crop management. No IP focused on issues like soil and water conservation or post-harvest innovations. We therefore define all IPs in Sudan Savannah as 'top-down' in terms of soil and fertility management (and crop management) technologies. Similarly, all IPs in Zimbabwe focus on soil and water conservation, so we view these IPs as top-down in terms of soil and water conservation. Note that we characterize IPs as top-down for specific technologies (and not as top-down overall). The reason is that IPs forced to focus on one technology may also decide to embrace another priority in a bottom-up manner.[30] Details about priorities per IP are provided in the Appendix Table A.3.3.

When exploring heterogeneous treatment effects at the IP level, we follow a simple methodology to improve the balance between treatment and control groups in terms of some household and village characteristics. Specifically, rather than using all 'clean villages' from the Action Zone as the control group, we now construct IP-specific control

[30] In total there are 28 IPs. Of these IPs, 4 IPs focus on soil and water conservation in a top-down fashion (=14%), In addition, 8 are top-down IPs in terms of soil and fertility management (=0.28%), 12 are top-down IPs in terms of crop management (42%), and 4 are top-down focusing on post-harvest technologies (14%).

groups by selecting households from (relatively) nearby clean villages (i.e. from the same or most nearby ward, depending on the PLS in question). Thus splitting our sample into smaller parts, we obtain more relevant comparisons of treatment and control households.[31]

3.4 Estimation results

We now turn to the regression results. The main results for question 1, regarding the impact of IAR4D on the adoption of selected innovations, are summarized in Table 3.3. We only report the results for the coefficients of interest, or the coefficient associated with the IAR4D treatment, but most models have been estimated using a full set of controls and fixed effects (details of the estimation strategy are provided at the bottom of the Table). The different rows in the Table correspond with different innovations (from soil and water conservation efforts to post harvest technologies), and the columns refer to the different models summarized in Section 3.3.2.

Across the board, the regression results of these pooled models provide little evidence of robust impact. The exception to the rule is the uptake of crop management innovations – across all models and samples we estimate we find a positive correlation between the presence of innovation platforms and the adoption of novel crop management techniques. This may reflect that crop management was identified as a priority across many IPs, so that a significant average treatment effect materializes. It could also reflect that innovations such as the application of (in)organic pesticides and intercropping are relatively easy compared to the more demanding innovations in other domains, or the presence of strong extension support on most of the platforms. We find no robust effects for soil management, or the prevention of post-harvest losses. However, and as argued, the lack of robust associations across the pooled data may obscure the existence of positive treatment effects at the level of specific IPs – those platforms were soil management or post-harvest losses were identified as a key bottleneck.

[31] For IP level analysis, we cannot determine the counterfactuals for *Musawa*, *Safana, Shanono, Bunkure, Wedza* and *Murewa*. Instead, we create pairs of IPs (*Musawa/Safana, Shanono/Bunkure and Wedza/Murewa*) for which we can determine close geographic counterfactuals. As a result, we report results for 25 IPs instead of 28 (see section 4).

Table 3.3: Summary table for outcome estimates of β^j_1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: totsw								
$\hat{\beta}_1^j$	0.0863	0.0651	0.0599	0.0643	0.0703	0.111	0.0953	0.0955
	(0.0977)	(0.101)	(0.0986)	(0.0995)	(0.0979)	(0.101)	(0.106)	(0.143)
N	5,725	5,417	5,417	5,354	5,354	5,354	4,192	4,192
Dependent variable: totsf								
$\hat{\beta}_1^j$	-0.123	-0.154	-0.107	-0.0953	-0.0329	-0.0555	-0.107	-0.108
	(0.126)	(0.133)	(0.107)	(0.107)	(0.103)	(0.107)	(0.110)	(0.148)
N	6,055	5,599	5,599	5,534	5,534	5,534	4,516	4,516
Dependent variable: totcm								
$\hat{\beta}_1^j$	0.267**	0.241**	0.286***	0.275***	0.272**	0.275**	0.313***	0.308*
	(0.114)	(0.116)	(0.105)	(0.106)	(0.106)	(0.112)	(0.118)	(0.159)
N	5,819	5,384	5,384	5,321	5,321	5,321	4,134	4,134
Dependent variable: totph								
$\hat{\beta}_1^j$	-0.164	-0.115	-0.0757	-0.0732	-0.0798	-0.125	-0.160	-0.158
	(0.159)	(0.160)	(0.153)	(0.154)	(0.143)	(0.145)	(0.157)	(0.215)
N	5,914	5,482	5,482	5,419	5,419	5,419	4,308	4,308
Methodology	Poisson	Poisson	Poisson	Poisson	OLS	OLS	OLS	OLS
Sample	Unbalance	Unbalanced & No missi controls	Unbalanced & No missi controls	Balanced Village& No missing controls	Balanced Village& No missing controls	Balanced Village& No missin controls	Balanced Household No missin controls	Balanced Household No missin controls
Controls	NO	NO	YES	YES	YES	YES	YES	YES
Action Zone	NO	YES	YES	YES	YES	NO	NO	NO
Village FE	NO	NO	NO	NO	NO	YES	YES	NO
Household FI	NO	NO	NO	NO	NO	NO	NO	YES

Notes: For Poisson estimations marginal impact estimates at mean levels are reported. N refers to the number observations used in the estimations. Robust standard errors clustered at village level in parentheses. We u household head's education, agricultural experience, age, gender and size of household as control variables wh indicated. *** p<0.01, ** p<0.05, * p<0.1

To probe the issue of heterogeneous treatment effects we examine the association between the adoption of innovations and the IAR4D treatment for a subsample of the data – for those villages where platform priorities match with the specific outcome variable. First, we investigate average treatment effects for all platforms in that subsample. Results shown in Table 3.4 are similar to those of the pooled model: treatment does not enhance the rate of adaption of technologies except for crop management technologies. However, within this subsample there may still be successful as well as unsuccessful IPs ones in terms of the implementation of the policies.

Table 3.4: Estimates for β^j_1 for IPs focused on agricultural technologies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: totsw							
$\hat{\beta}_1^j$	0.274	0.249	0.228	0.233	0.255	0.252	0.275	0.277
	(0.215)	(0.223)	(0.224)	(0.229)	(0.225)	(0.231)	(0.261)	(0.354)
N	1,711	1,621	1,621	1,582	1,582	1,582	1,202	1,202
	Dependent variable: totsf							
$\hat{\beta}_1^j$	-0.201	-0.310	-0.243*	-0.236	-0.0743	-0.110	-0.149	-0.167
	(0.170)	(0.197)	(0.147)	(0.147)	(0.130)	(0.137)	(0.135)	(0.179)
N	3,184	2,846	2,846	2,837	2,837	2,837	2,328	2,328
	Dependent variable: totcm							
$\hat{\beta}_1^j$	0.221	0.173	0.211*	0.213*	0.205*	0.193	0.219	0.213
	(0.140)	(0.148)	(0.122)	(0.122)	(0.122)	(0.131)	(0.136)	(0.184)
N	3,874	3,571	3,571	3,564	3,564	3,564	2,866	2,866
	Dependent variable: totph							
$\hat{\beta}_1^j$	-0.567	-0.570	-0.538	-0.526	-0.452	-0.459	-0.435	-0.425
	(0.421)	(0.421)	(0.414)	(0.417)	(0.273)	(0.281)	(0.292)	(0.399)
N	1,237	1,227	1,227	1,220	1,220	1,220	1,084	1,084
Methodology	Poisson	Poisson	Poisson	Poisson	OLS	OLS	OLS	OLS
Sample	Unbalanced	Unbalanced & No missing controls	Unbalanced & No missing controls	Balanced Village& No missing controls	Balanced Village& No missing controls	Balanced Village& No missing controls	Balanced Household& No missing controls	Balanced Household& No missing controls
Controls	NO	NO	YES	YES	YES	YES	YES	YES
Act. Zone FE	NO	YES	YES	YES	YES	NO	NO	NO
Village FE	NO	NO	NO	NO	NO	YES	YES	NO
Hous. FE	NO	NO	NO	NO	NO	NO	NO	YES

Notes: For Poisson estimations marginal impact estimates at mean levels are reported. N refers to the number of observations used in the estimations. Robust standard errors clustered at village level in parentheses. We use education, agricultural experience, age, gender of household head, and size of household as control variables when indicated. *** p<0.01, ** p<0.05, * p<0.1

To explore whether there are successful IPs, we examine IP level treatment effects in this subsample Results are summarized in Table 3.5, and again are rather mixed. Each row in the Table corresponds with a specific IP, and for each IP we have estimated whether it has been successful in promoting the adoption of innovations in its priority domain. For example, for the *Kubau* platform we did not find reference to our priority areas in platform documents[32], but the *Dandume* platform intended to focus on soil and water management and soil fertility management. According to our models, it successfully enhanced the adoption of innovations in the former domain, but was unable to boost adoption of soil fertility innovations (relative to the control group). According to Table 3.5, no IP was able to improve the adoption of post-harvest innovations. However, two IPs increased the

[32] In fact, in *Kubau*, the focus was on livestock technologies which are not the scope of this paper.

uptake of innovations in soil and water management (*Dandume* and *Balaka*), one IP increased the adoption of soil fertility innovations (*Ikara*, but two other platforms apparently lowered the uptake of innovations), and five IPs increased crop management adoptions (*Ikara, Madarounfa, Musawa, Kituva, Chahi*). In what follows we consider these platforms as 'successful' IPs: *Dandume, Ikara, Madorounfa, Kituva, Chahi, Balaka, Musawa* and *Safana.* Casual inspection of the results suggests that older platforms – operational for two years rather than one year – are more likely to be successful than younger ones.[33] Arguably this reflects both the extra "time to achieve impact" as well as the effect of platform maturity, or the extent to which it is able to function as intended.

This result may also imply that IAR4D may reduce poverty through promoting agricultural technology adoption. 2 IPs from Lake Kivu PLS, Kituva and Chahi, which are successful at promoting technology adoption, have also been successful at bringing down poverty at Lake Kivu PLS (see Table 2.6 in Chapter 2). Hence there is (limited) evidence suggesting that there is a correlation between the success in technology adoption and poverty reduction.

Are the benefits of platforms shared widely within treatment communities, or is a subsample of village members able to capture most of them? We start analyzing this question in Table 3.6, where we report coefficients of the relevant interaction term (see 3.3.4). We seek to explain whether adoption rates vary with the level of education of the household head – a leading candidate variable for conditional impacts. We find no robust evidence that adoption rates vary across education levels. To economize on space, we do not report estimates for other household characteristics we have considered (such as such as age and gender of the household head, years of experience in farming, household size) but the same is mostly true (the estimates are available upon request).[34] It appears that the benefits of IAR4D in terms of enhanced adoption, if any, are widely shared within the community.

[33] It is also important to note that the power of IP level estimates is relatively low because we only have few observations. Hence, we are vulnerable to type II errors: to falsely conclude that there is no treatment effect, even if there actually is one.
[34] There are only two exceptions to this. First, in soil and fertility management and crop management domains experienced households adopt more technologies as a result of intervention. Second, it seems that larger households benefit more from the treatment in the adoption crop management technologies.

Table 3.5: IP level estimates for β^j_1 for IPs focused on agricultural technologies

Action Zone	IP	totsw		totsf		totcm		totph		Field time	IP time (years)
		$\hat{\beta}_1^*$	N	$\hat{\beta}_1^*$	N	$\hat{\beta}_1^*$	N	$\hat{\beta}_1^*$	N		
All sample	All sample	0.228	1,621	-0.243*	2,846	0.213*	3,564	-0.538	1,227	1.6	2.1
NGS	Kubau									1.5	2
	Kudan	-0.553	146			0.0464	143			2.5	2
	Dandume	0.906***	153	-0.0575	162					2.5	3
	Ikara			0.661*	157	1.409***	154			2.5	3
Sahel	Aguie			-0.270	171	0.273	173			2.5	2
	Zangon daura									0.5	2
	Madarounfa			-0.293	187	1.514**	187			2.5	3
	Guidan roumdji			0.439	176					2.5	3
Sudan	Shanono/bunkure			-1.957	265	-0.666	259			2.5	2
Savanah	Musawa/safana			0.703	250	1.434***	245			2.5	2
DRC	Bweremana			-0.548	269	-0.836*	214	-0.508	240	1.5	3
	Rumangabo			-0.228	341	0.0332	297	-0.00154	312	1.5	2
	Kituva			-0.475	154	4.005***	127	0.745	142	1	1
	Rubare			-0.536**	183	0.137	155	-0.333	168	1	2
Rwanda	Mudende			-1.303**	163	-0.493	160			1	2
	Remera									1	1
	Gataraga			0.285	368	0.163	363	-0.279	365	1	2
	Rwerere									1	1
Uganda	Kayonza	-0.208	159			-0.194	153			1	2
	Chahi					0.900***	381			1.5	2
	Bufundi	-0.188	382			0.0373	381			1.5	2
	Bubare					-0.149	179			1	3
Malawi	Balaka (CA)	0.736***	194							1	2
Mozambique	Bariue (CA)	0.0197	220							2	2
Zimbabwe	Wedza/Murewa	-0.202	367							1	2

Notes: Marginal estimates at mean levels for Poisson regression same as column (3) of Table 3.3 are reported in the Table. Robust standard errors clustered at village level are in parentheses. We use education, agricultural exp., age, gender of household head and size of household and action zone dummies as control variables in all the estimations. *** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Summary table for count data outcome estimates of α^j_1-Education

	(1)	(2)	(3)	(4)	(5)	(6)
			Dependent variable: totsw			
$\hat{\alpha}_1^j$	2.25e-05	-0.0604	0.148	0.102	0.288	0.366
	(0.379)	(0.382)	(0.383)	(0.400)	(0.446)	(0.589)
N	1,621	1,582	1,582	1,582	1,202	1,202
			Dependent variable: totsf			
$\hat{\alpha}_1^j$	0.101	0.0878	0.0417	-0.0363	-0.805***	-0.727*
	(0.298)	(0.299)	(0.268)	(0.282)	(0.280)	(0.417)
N	2,846	2,837	2,837	2,837	2,328	2,328
			Dependent variable: totcm			
$\hat{\alpha}_1^j$	-0.00153	-0.00739	0.00795	-0.00506	0.390	0.404
	(0.217)	(0.217)	(0.219)	(0.229)	(0.265)	(0.391)
N	3,571	3,564	3,564	3,564	2,866	2,866
			Dependent variable: totph			
$\hat{\alpha}_1^j$	1.609***	1.552***	0.267	0.109	-1.616***	-1.642**
	(0.540)	(0.542)	(0.339)	(0.361)	(0.413)	(0.649)
N	1,227	1,220	1,220	1,220	1,084	1,084
Methodology	Poisson	Poisson	OLS	OLS	OLS	OLS
Sample	Unbalanced & No missing Controls	Balanced Village& No missing controls	Balanced Village& No missing Controls	Balanced Village& No missing controls	Balanced Household& No missing Controls	Balanced Village& No missing controls
Controls	YES	YES	YES	YES	YES	YES
Action Zone FE	YES	YES	YES	NO	YES	NO
Village FE	NO	NO	NO	YES	YES	NO
Household FE	NO	NO	NO	NO	NO	YES

Notes: For Poisson regressions marginal impact estimates at mean level are reported in the table. Robust standard errors clustered at village level are in the parentheses. We use education, agricultural experience, age, gender of household head, and size of household as control variables when indicated. *** p<0.01, ** p<0.05, * p<0.1

Finally, we tentatively examine the issue of heterogeneity at the platform level (see 3.3.5). We ask whether the duration of the platforms (years in the field) matters for adoption patterns and whether the success of platforms varies with initial social capital or village resources variables.[35] Simple correlation statistics shown in Table 3.7 indeed suggest this is the case, for a sub-sample of these village level variables. As reported above, successful IPs tend to be established earlier, suggesting that it takes some time for these platforms to mature and deliver impact. On average, successful IPs are 0.54 years older, which is statistically significant (*t*-statistics=1.79). Similarly, successful IPs are

[35] The impact of platforms also varies systematically with the composition of the platform. However, since platform composition is arguably endogenous, we will leave this question for future research.

characterized by higher scores on our local cooperation index (0.52 points higher on a 4 point scale, associated *t*-statistics=2.07), and are more likely to have a common place for worship (probability is 20% higher, associated *t*-statistics=1.95).[36] These findings suggest that 'platform maturity' and social capital explain some of the variation in platform performance. This is confirmed in complementary regression analysis where we include the various household and community controls, and split the sample according to the age of the platform (older or younger than 2 years), the level of cooperation in the village, or the presence of a worship place. Details of these regression models are available on request.

Table 3.7: Estimates of correlations between IP successes and selected IP and village characteristics

	IP activity in the field (years)	Cooperation among people (0-4)	Worship place at the village (0/1)
Success (0/1)	0.540*	0.523*	0.200*
	(0.301)	(0.253)	(0.103)
N	25	22	22

Notes: Estimates are from IP level estimation of simple linear regressions success is explanatory variable, and village or IP characteristics are dependent variables. As numbers of estimates are limited, we do not control for household characteristics, action zone, village and household fixed effects. Since there is no available information of cooperation among people and worship places for 3 IPs, estimations are conducted for 22 IPs. Standard errors are in the parentheses. *** p<0.01, ** p<0.05, * p<0.1

[36] There are no significant correlations platform success and the remaining village-level variables (details are available on request). Again, however, it is important to reiterate that the power of these t-tests is quite low as the analysis is at the IP level. Thus, again, the risk of type II errors looms large, and we can only identify the conditional impact of those baseline factors that have a very large effect on the likelihood of IP success

Table 3.8: Impact estimates for 'top-down' and 'bottom up' platforms

Dependent variable:	totsw		totsf		totcm		totph	
	Bottom-up	Top down	Bottom-up	Top down	Bottom-up	Top down	Bottom-up	Top down
$\hat{\beta}_1^j$	0.224	-0.202	-0.0232	-0.458*	0.440*	0.0435	-0.279	-0.0193
	(0.219)	(0.317)	(0.161)	(0.237)	(0.226)	(0.139)	(0.277)	(0.368)
N	1,254	367	1,384	1,462	1,180	2,391	365	862
Methodology	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
Sample	Unbalanced& No missing controls	Unbalanced& No missing controls	Unbalanced& No missing Controls	Unbalanced& No missing controls	Unbalanced& No missing controls	Unbalanced& No missing controls	Unbalanced& No missing controls	Unbalanced& No missing controls
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Action Zone FE	YES	YES	YES	YES	YES	YES	YES	YES
Village FE	NO	NO	NO	NO	NO	NO	NO	NO
Household FE	NO	NO	NO	NO	NO	NO	NO	NO

Marginal estimates at mean levels for Poisson regression same as column (3) of Table-3. Bootstrap standard errors clustered at village level in parentheses. We use education, agricultural experience, age, gender of household head and size of household and action zone dummies as control variables in all the estimations. *** p<0.01, ** p<0.05, * p<0.1

Finally, we ask whether the success of IPs depends on platform implementation—in particular the degree of top-down planning. The lack of local variety in priorities may be interpreted as a sign of top-down priority-setting (an open question, admittedly), we may probe whether top-down planning is associated with platform success. We detect some patterns in the data supporting the view that local variation in priority setting might be beneficial for IAR4D impact—taskforces with variation in priorities across IPs seem to do a better job in promoting the adoption of innovations than taskforces that lack such variability. In Table 3.8, we compare estimates for 'top-down' and 'bottom-up' IPs for each technology domain. Specifically, the adoption rate of crop management technologies is significantly higher in IPs characterized by bottom-up priority setting. Also note that the adoption of soil fertility innovations is significantly lower in IPs characterized by top-down priority setting. These outcomes are consistent with the interpretation that allowing platforms to capitalize on local knowledge about preferences and constraints (i.e., promoting flexibility) improves platform performance. However, and as mentioned, we acknowledge that the link between top-down planning and reduced diversity in priorities is tenuous, and debatable. Therefore we emphasize that these findings should be seen as tentative, and as an invitation for additional research in this issue.

3.5 Conclusions and discussion

Conventional extension efforts have produced disappointing results, and have failed to promote the adoption of agricultural innovations. Pamuk et al. (2014a) provide early evidence that alternative mechanisms, based on the innovation system perspective to innovation and diffusion, are better able to promote agricultural development and reduce rural poverty. In this paper we examine the mechanisms behind that finding, and try to open the black box linking innovation platforms to poverty alleviation. We emphasize that the impact assessment is based on an analysis of baseline and midline data, collected only one or two years after establishment of the platforms. This implies that insofar as impact varies with platform maturity, and it takes time for platforms to mature, we may be underestimating the genuine long-term impact. Future research will be necessary to shed light on this issue.

Our main conclusions are twofold. First, while some types of innovations are robustly associated with the creation of innovation platforms – namely innovations in the domain of crop management – the same is not true for innovations in other domains. Specifically, it appears as if the demand for innovations in the domains of soil fertility management, soil and water management, and post-harvest management are much more context-specific – varying across space. A standardized, top-down innovation agenda is therefore unlikely to fit, and priority setting at the local level seems to be better able to capture this need for diversity. Second, while we find no evidence of heterogeneous treatment effects at the level of individual households – successful platforms seem to encourage the adoption of innovations across various social groups – we also find that the success of platforms is heterogeneous. That is; some platforms "work" and promote the adoption of innovations, and others do not (yet). This may not be surprising in light of the immature status of many of the platforms (midline data collected one or two years after platforms were created).[37] We also find that the success of interventions varies with some measures of ex ante social capital and the quality of platform implementation (especially the degree to which local, tailor-made problem diagnosis and priority setting is facilitated). This provides scope for both improved targeting, and room for operational improvements when rolling out the decentralized innovation agenda.

We believe evidence suggests that the decentralized approach to promoting innovation and adoption hold promise, and needs to be considered as an alternative to dominant extension modalities. However, two caveats are relevant. First, we only find a positive and significant effect for one technology domain, and there is considerable heterogeneity in the results at the IP level. While we provide tentative evidence regarding the factors determining the success of IPs, identifying the institutional, technological or organizational factors that determine the performance of IPs should be a priority. Second, we are aware of the trade-offs associated with such a transition from central to decentralized approach. Decentralized approaches such as IAR4D facilitate capitalizing on local knowledge and understanding, but may also involve foregone economies of scale in

[37] Anecdotal evidence supports the idea that platform maturity matters. One program member described to us how successful IPs go through phases – from "forming" to "storming" to "norming" as he phrased it. High performance may not be expected until later stages are reached.

R&D. Moreover, too much emphasis on decentralized approaches could imply a focus on bottlenecks that can be addressed locally – not necessarily the most binding constraints to agricultural development (which may require sectoral policy reform). Arguably the most successful strategy to unleash agricultural productivity on African involves integrating the local and the macro perspective. Currently, in many African countries the balance appears skewed towards the latter.

3.A Appendix: Additional tables

Table A.3.1: Agricultural technologies considered each count data outcome variables

Soil and Water Management Innovations
- Mulching
- Trenches and Terraces
- Water Harvesting
- Irrigation
- Conservation Farming
- Other

Soil and Fertility Management Innovations
- Animal Manure
- Cover Crops
- Crop Rotation
- Intercropping
- Rhizobia Inoculation
- Chemical Fertilizer
- Other

Crop Management Innovations
- Row Planting
- Plant Spacing
- Organic Pesticides
- Inorganic Pesticides
- Other

Post Harvest Innovations
- Drying
- Threshing/Shelling Equipment
- Improved Storage Facilities
- Pest Control
- Grading
- Other

Table A.3.2: Descriptive statistics of dependent and explanatory variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
Totsw	5725	1.14	1.20	0	5
Totsm	6055	2.48	1.48	0	6
Totcm	5819	1.83	1.44	0	5
Totph	5914	2.22	1.50	0	6
Gender	6146	0.76	0.43	0	1
Age	6167	47.29	14.63	16	105
Education	5820	0.20	0.40	0	1
Household size	6155	8.62	8.57	0	275
Experience	6100	24.48	14.66	0	80

Table A.3.3: Distribution of IPs by PLSs and Action Zones

PLS	Action Zone	Total Number of IPs	Total number of IPs that set corresponding technology domain as a priority: Soil and water conservation	Soil and Fertility Management	Crop Management	Post Harvest
KKM	**NGS**	4	2	2	2	0
	Sahel	4	0	3	2	0
	Sudan Savannah[1]	4	0	4	4	0
Lake Kivu	**DRC**	4	0	4	4	4
	Rwanda	4	0	2	2	1
	Uganda	4	2	0	4	0
ZMM	**Malawi**	1	1	0	0	0
	Mozambique	1	1	0	0	0
	Zimbabwe[1]	2	2	0	0	0
Total		28	8	15	18	5

[1] For this two action zones, we pair the IPs accordingly as explained in footnote 6 in the text. Hence, for Sudan Savannah and Zimbabwe, we have 2 and 1 IP pairs respectively.

Chapter 4

Implementation matters: Heterogeneity in the impact of decentralized innovation systems in Africa[¥]

4.1 Introduction

Agricultural growth is considered an important factor for sustainable alleviation of poverty (Haggblade et al. 2007; Ligon & Sadoulet 2007; World Bank 2007; Christiaensen et al. 2011). Policy makers have applied a wide variety of strategies to boost agricultural productivity and production in developing countries. A relatively new view in those strategies is the implementation of the innovation system perspective to support agricultural research and development for resource-poor farmers. The innovation system approach is a multi-stakeholder and participatory method integrating the knowledge of stakeholders from the value chain via so called "innovation platforms (IPs)". At IPs, the stakeholders are expected to come together to find solutions to local bottlenecks and to design and implement policies at the local level (Leeuwis & Van den Ban, 2004; Hall et al. 2006; Knickel et al. 2009). Many IPs have recently been introduced to enhance agricultural production and productivity of resource poor farmers through adoption of suitable and efficient agricultural techniques (Nederlof et al. 2011).

Few evaluation studies have quantitatively explored the impact of these IPs. Exceptions are studies that assessed the effect of the Sub Saharan African Challenge Program (SSA CP). The SSA CP adopted the Integrated Agricultural Research for

[¥] This Chapter is based on following research paper: Pamuk, H. & van Rijn, F. (2014). *Implementation Matters: Heterogeneity in the Impact of Decentralized Innovation Systems in Africa* . Unpublished manuscript

Development (IAR4D) approach as its main philosophy through the implementation of local decentralized IPs. Chapter 2 shows that, on average, the program does not have an impact on food consumption. Chapter 3 and van Rijn and Nkonya (2012) also suggest that IPs have mixed impact on agricultural innovation and household social capital respectively.. Moreover, the outcomes at IP level are highly variable: ranging from significantly positive to non-significant to significantly negative.

The policy evaluation literature suggests two answers to explain differences in impact at the IP level. First, the impact of any policy may be a function of characteristics of the region where the project is implemented (Heckman et al. 1997; Deaton 2010). Second, even if the policy is implemented among the same population, its outcomes may still vary if the policy is implemented by different organisations; the organisations may possess different organisational and managerial capacities and have different efficiency levels (Heckman et al. 1997; Deaton, 2010; Allcott & Mullainathan 2012; Bold et al. 2013). The aforementioned studies evaluating the impact of IPs investigate the first factor: heterogeneity across target populations. This paper investigates the role of the latter: heterogeneity in implementation.

We explore heterogeneity in implementation of the SSA CP, and the effects thereof on program impact. We argue that differences in program impact might be explained by the extent to which IPs actually adopted the core principles of IAR4D. The objective of this Chapter is twofold. First, to capture heterogeneity in implementation, we quantify the IAR4D principles and summarise them into an overall “IAR4Dness” index. Second, we analyse whether differences in impact result from differences in the level of IAR4Dness.

We analyse differences in impact by using data from West, Central and Southern Africa collected by SSA-CP (used in Chapter 3) and econometric techniques as well as correlation analysis. The way IAR4D approach implemented by innovation platforms may be correlated with (1) the baseline characteristics 2) change in those characteristics (e.g. poverty, income, FCS, and etc.) during the implementation. To control for these confounding factors, we utilize the panel feature of our data set, many control variables, and use an instrumental variables approach.

Results indicate that implementation matters. IAR4Dness is positively related to food security of intended beneficiaries, our main outcome variable after controlling for regional time trends. We find that attendance of stakeholders in program activities – in particular to information sharing activities and field visits – determines how successful IPs are in increasing household food consumption. Although our results do not explain entire IP level heterogeneity in program impact on food consumption, which is found in Chapter 2, they explain some part of the it within each region or country: Being other factors are constant, we observe higher food consumption score for the IPs at which attendances to the field and information sharing activities are higher. Nevertheless, we do not find evidence that this relationship results from the adoption of agricultural technologies, marketing strategies or changes in levels of household social capital - three of the potential impact channels.

This paper is organized as follows. Section 4.2 gives a brief conceptual framework including a description of the Sub Saharan African Challenge Program. In section 4.3 we present our data set. In section 4.4, we describe the IAR4Dness indices, explain how they differ across IPs, and discuss their correlation with baseline characteristics of innovation systems. Section 4.5 introduces the identification strategy. In section 4.6, we analyse whether the index explains differences in impact of the IPs on food security and discuss robustness of the results. In Section 4.7, we explore whether the impact of IAR4Dness stems from selected intermediate outcomes. Finally, Section 4.8 concludes.

4.2 Conceptual framework

IAR4D was introduced as part of the SSA CP in 2004. The approach is based on the paradigm of innovation systems. According to this perspective, innovation is the result of the integration of knowledge from various actors and stakeholders (e.g. Leeuwis & Van den Ban 2004) . With IAR4D this approach was shaped by the creation of decentralized IPs; coalitions of stakeholders to identify and address local bottlenecks to agricultural development. Representatives of farmers' associations, traders, researchers, extension workers, NGOs, and government policy makers regularly meet at these platforms, articulate their views, and negotiate joint strategies for action (FARA 2008). [38]

To promote external validity, IAR4D was implemented in three African project learning sites (PLSs): (*i*) "Lake Kivu (LK)" in Eastern and Central Africa, (*ii*) "Kano-Katsina-Maradi (KKM)" in West Africa, and (*iii*) "Zimbabwe-Malawi-Mozambique (ZMM)" in Southern Africa. Each region was divided into three sub-regions and in each sub region 4 IPs were implemented covering various villages. In total, 32 IPs became operational.[39] The overall program has been coordinated by the Forum for Agricultural Research in Africa (FARA). However, different agencies have been responsible for the implementation and facilitation of the IPs (see Appendix 5.1 for an overview).

IPs had to fulfil five criteria to abide with the IAR4D approach (FARA 2008; Hawkins et al. 2008): (1) IPs should be representative, inclusive and with diverse partnerships, (2) there should be non-linear, collective and collaborative interaction among IP actors, (3) research addresses key constraints and opportunities agreed upon by IP members in the context of entire value chains, (4) the research process is multidisciplinary and participatory, and (5) there is institutional and human capacity building for IAR4D actors to effectively participate. We define the extent to which IPs abide with these criteria "in the field" as the level of "IAR4Dness". Because of the decentralized nature of the IPs and the different implementing agencies, we expect to find variation in the level of IAR4Dness across platforms.

As explained by Pamuk et al. (2014a), Pamuk et al. (2014b) and van Rijn et al. (2012), the IAR4D approach as implemented may have an impact on poverty through increased agricultural technology adoption, changes in marketing strategies, and increased levels of social capital. Adoption of modern technologies is a candidate channel through which IAR4D could enhance agricultural production and reduce poverty. Agricultural innovation can have a direct influence on agricultural production by increasing

[38] Please see section 2.3 for further details of the program.
[39] Although 36 IPs were to be established 4IPs in ZMM never became operational and data were not collected for those IPs.

productivity, by decreasing production cost, or by reducing risk associated with adoption (De Janvry & Sadoulet 2002). Changing marketing strategies is another important intermediate outcome of the IAR4D policy. This could enable specialization and the creation of surpluses. However, the immediate impact of IAR4D is perhaps not to directly influence agricultural technology or marketing strategies, but to create an enabling setting in which such intermediate outcomes may materialize (see van Rijn et al. 2012 for an overview of why social capital and agricultral innovation are naturally linked). Therefore, household social capital measuring the interaction of households with other agents is also considered an important intermediate outcome variable, which is in line with the innovation system perspective.

4.3 Data description

4.3.1 Sample

The IAR4D program was implemented as a large experiment, where some communities "received" IPs (treatment communities) and others did not (control communities). Even though details of the sampling design vary slightly across the different regions, it generally followed a randomized controlled trial approach (see FARA 2009; Pamuk et al. 2014b for details on the sampling frame). Within each village, a random sub-sample of 5-15 respondents (households) was drawn from treatment and control villages. Baseline and midline data were collected at village and household level in 2008/2009 and 2010/2011. In this chapter, as in chapter 3, we use data from all PLSs. This includes the data from Lake Kivu, used in Chapter 2. However, we now focus on the subsample of treatment villages because we are interested in differences in impact within these treated communities. Hence we do not use data from conventional and control villages.

4.3.2 IAR4Dness

To determine the level of IAR4Dness we used the data collected in a small survey among IP coordinators by e-mail in mid-2012 (see Appendix 2 for details of the survey).[40] This

[40] All IP coordinators responded to the e-mail.

survey included questions capturing the extent to which the five IAR4D principles were respected during the implementation stage. The first principle is captured by the number of different types of stakeholders involved.[41] The second principle was captured by the level of involvement of the stakeholders in different activities, and the variance in involvement of different types of stakeholders. The third principle was captured by the percentage of different stakeholders involved in problem identification and the percentage of problems prioritized and acted upon. The fourth principle was captured by stakeholders' involvement and implementation of activities and the percentage of different stakeholders involved in the policy design. The fifth indicator was captured by stakeholders' involvement in capacity building activities including information sharing, training and field visits. For all indicators we calculate the average of those stakeholders involved and/or those problems identified, and normalise data from 0 to 100. Summary statistics are provided in Table 4.1, where higher values mean higher scores in terms of IAR4Dness, and Figure 4.1 shows detailed distributions for the variables. We observe that in particular Principle 2a and Principle 4a has very similar distribution and overlap with each other.

4.3.3 Outcome variables

Lacking income data for various IPs, we use household food security as our main outcome variable (see Panel A of Table 4.2). We use agricultural technology, marketing strategies, and household social capital variables as intermediary outcome variables (see Table A.4.3 in the Appendix for details). To measure household food security, we employ the Food Consumption Score (FCS) index measuring weekly consumption of food items, weighted by the nutritional value added. To test the mechanism behind the impact of IAR4Dness on food security, we use three different sets of dummy variables for agricultural technology adoption, marketing strategies and social capital variables.

[41] Stakeholder include farmers, researchers, extension agents, marketing organisations, policy makers, NGOs, input suppliers, traders, private businesses and others.

Table 4.1: IAR4Dness variables

Principle	Definition	Obs.	Mean	Std.	Min	Max
Principle 1	Number of different stakeholders involved	32	75.3	14.9	50.0	100.0
Principle 2a	Average involvement in listed activities	32	78.0	13.6	54.5	100.0
Principle 2b	Difference to average participation*	32	76.6	17.1	27.1	100.0
Principle 3a	% Of stakeholders involved in problem identification	32	32.6	19.9	8.3	100.0
Principle 3b	% Of problems identified being prioritized and addressed	32	100.0	0.0	100.0	100.0
Principle 4a	Average involvement joint planning and implementation	32	77.3	13.1	54.5	100.0
Principle 4b	% Of stakeholders involved in policy formulation	32	45.4	26.7	8.3	100.0
Principle 5	Average involvement in information sharing and field visits	32	77.3	16.3	44.0	100.0

Note: all variables are normalised in the range [0,100]

*this indicator is rescaled so that smaller variances (more equality) is reflected by higher scores

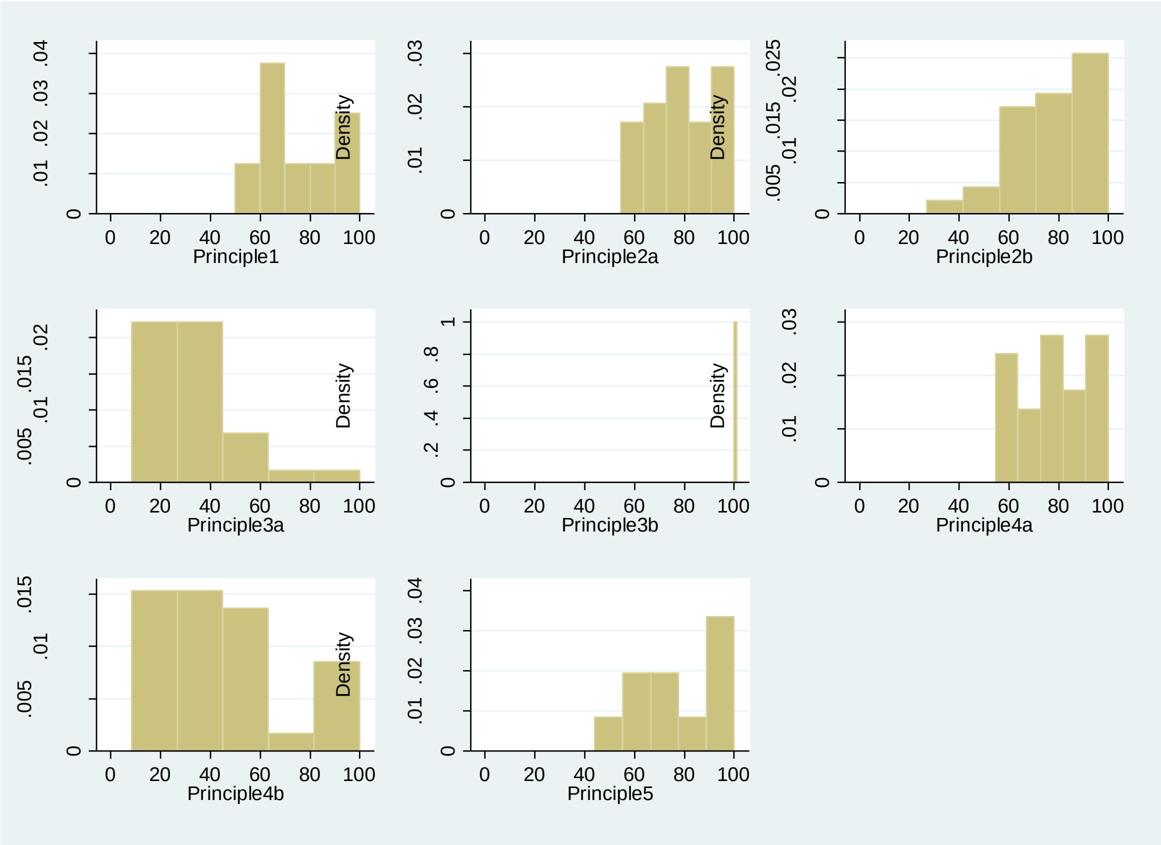

Figure 4.1: Distribution of the Principles

Table 4.2: Outcome variables and household, village and social capital variables

Variable	Definition	Obs†	Mean	Std.	Min	Max
Panel A: Outcome variables						
FCS	Weekly food consumption score	3322	48.0	21.4	0	108.5
Panel B: Household characteristics						
gender	Equals to 1 if household head is male, 0 otherwise	3456	0.7	0.4	0	1
Age	Age of household head	3433	46.6	14.7	16	105
Education	Education level of household head	3242	3.3	2.3	1	10
Size	Household size in logarithms	3436	1.9	0.6	0	4.8
Panel C: Village Characteristics						
school	Equals to if there is a school at the village, 0 otherwise	332	0.66	0.47	0	1
hospital	Equals to if there is a hospital at the village, 0 otherwise	322	0.30	0.46	0	1
worship	Equals to if there is a worship place at the village, 0 otherwise	339	0.81	0.39	0	1
socialhall	Equals to if there is a social hall at the village, 0 otherwise	302	0.22	0.42	0	1
roads	Equals to if village is connected with weather road(s), 0 otherwise	315	0.73	0.44	0	1
mobilenetwork	Equals to if village has mobile network connection, 0 otherwise	336	0.88	0.33	0	1
Panel D: Village social capital						
Participation	Participation in community activities (0-4)	129	2.8	1.0	0	4
Trust	Extent of trust among people (0-4)	128	2.6	1.0	0	4
Cooperation	Cooperation among people (0-4)	126	2.7	1.0	0	4
Gift exchange	Extent of giving or exchanging gifts (0-4)	130	2.2	1.1	0	4
Contrcomm	Extent of financial contribution for community activities/problems (0-4)	130	2.4	1.2	0	4
Contributgr	Extent of financial contribution to group activities (0-4)	128	2.3	1.2	0	4
Helping	Spirit of helping others especially the poor (0-4)	129	2.0	1.4	0	4
Conflicts	Extent of settling conflicts or disputes among people (0-4)	128	2.9	1.0	0	4
Norms	Extent of abiding by the norms and byelaws (0-4)	131	2.6	1.1	0	4
Womenconfid	Women confidence to speak in public (0-4)	131	2.5	1.0	0	4
Consdwomen	Men's respect and consideration of women (0-4)	131	2.7	1.0	0	4
Panel E: Instruments						
Dyearinfield	Equals to 1 if number of years passed after the IP started field activities is more than 1.5, 9 otherwise	32	0.34	0.48	0	1

Notes: We report number of households and villages for the outcome variables/household characteristics and village characteristics/social capital variables respectively. For instruments, numbers of IPs are shown.

4.3.4 Household and village characteristics

To control for differences in IP context, and for the potential influence on project implementation, we use various household and village level variables (see Panel B and C of

Table 4.2). Our household level variables include gender, age, formal education level of household head, and household size. Our village level variables include a list of village amenities. To explore whether the level of cohesion in the community affects IP performance we include a third set of variables, namely baseline village social capital (Panel D of Table 4.2). These are different indicators than the social capital outcome variable mentioned earlier, which was measured and defined at the household level. Information regarding village level social capital was collected during community discussions by asking participants to evaluate social cohesion in their village (on a 0-4 point scale). These questions do not include information about interaction of villagers with others. Instead, they measure the quality of and order in social life.

4.4 Constructing an "IAR4Dness" index

We used three approaches to capture the level of IAR4Dness at the IP level. IAR4Dness is an aggregate index of the indicators, or an unweighted average of the five Principles. This reflects the idea that IAR4Dness is best captured by the different components rather than by its separate components. However, we also want to explore whether certain components matter more. Therefore, we also decompose the aggregate IAR4Dness index into the five principles listed before. This means we create a principle-specific average of principle 2a and 2b, 3a and 3b, and 4a and 4b. A third, and more data-driven approach, is to look at correlation between the different IAR4Dness variables, and create new components based on factors extracted via principal factor analysis. The number of factors (components) is determined by the variance extracted within each factor, or eigenvalue. According to the Kaiser criterion, only factors with an eigenvalue above 1 are retained. We use a varimax rotation method to maximize the variance across factors (see Kaplan 2008 for more technical details).

The IAR4Dness indices are presented in Table 4.3. The table reports the descriptive statistics for IAR4Dness, principle specific averages and factor variables - Principles 1 and 5 have also been reported in Table 4.1. There is little variance in aggregate IAR4Dness index, with a mean of 0.74 and a standard deviation of only 0.07. However, there is more variation when zooming in on individual principles, indicating some differences implementation across IPs. The factor analysis results in two factors (see Appendix 5.2). The first factor mainly captures participation in activities organised by the IP. The second factor captures the number of stakeholders involved and equality of involvement. Both factors are also correlated with the percentage of stakeholders involved in problem identification or policy formulation –albeit negatively. This indicates that, perhaps not surprising, even though more stakeholders are involved in the IP, not all stakeholders are represented when it comes to problem identification or policy formulation.

Table 4.3: IAR4Dness indices

Variable	Definition	Mean	Std.	Min	Max
IAR4Dness	Aggregate index	71.5	7.4	55.6	82.4
Principle 1	Representative, inclusive and diverse	75.3	14.9	50.0	100.0
Principle 2	Non linear, collective and collaborative	77.3	11.4	54.3	94.9
Principle 3	Key constraints and opportunities addressed	66.3	10.0	54.2	100.0
Principle 4	Multidisciplinary and participatory	61.3	16.0	41.4	96.8
Principle 5	Capacity building	77.3	16.3	44.0	100.0
Factor 1	Increase with participation in activities and decrease with involved in problem identification.	0.0	1.0	-1.7	1.8
Factor 2	Increase with # of stakeholders and decrease with involvement in policy formulation	0.0	1.0	-2.5	1.6

4.5 Correlation analysis

To investigate which factors explain the general variation in the change in FCS and IAR4Dness variables and check the exogeneity of the project implementation quality to baseline characteristics, we examine the IP level correlation between (1) the change in FCS and IP characteristics and (2) the quality of project implementation and IP characteristics in this section.

For the first correlation analysis, we calculate the change in FCS by subtracting midline IP level average of FCS from baseline IP level averages and estimate its correlation with IAR4Dness variables, baseline household and village characteristics at IP level and regional dummies. Table 4.4 reports the pair-wise correlation coefficient estimates between the change in FCS and those variables. The results shows that the change in FCS is positive and significant at the IPs where duration of field activities are longer, share of male household head and larger household size are higher, and spirit of helping and abiding to the norms and bylaws are more developed. In addition it seems that there is regional correlation in the direction of change in FCS at IP level as the correlation estimates are high and statistically significant for DRC and Sudan Savannah.

Table 4.4: Pair-wise correlation estimates for the change in FCS (ΔFCS) and selected variables

IP characteristics	
IAR4Dness	0.03
Principle 1	-0.27
Principle 2	-0.19
Principle 3	0.12
Principle 4	0.24
Principle 5	0.13
Year in field	0.51*
Household characteristics	
Gender	-0.33*
Age	0.26
Education	0.12
Size	0.30*
Village Amenities	
School	0.27
Hospital	0.21
Worship	0.13
Socialhall	-0.12
Roads	0.30
Mobile network	-0.07
Village social capital	
Participation	0.24
Trust	0.16
Cooperation	0.09
Gift exchange	0.24
Contrcomm	0.27
Contributgr	0.31
Helping	0.40*
Conflicts	0.22
Norms	0.32*
Women confid.	0.10
Consd. women	0.31
Regions	
DRC	-0.34*
Malawi	-0.18
Mozambique	-0.24
Norther Guinea Savannah	0.18
Rwanda	0.02
Sudan Savannah	0.44*
Sahel	0.10
Uganda	-0.09
Zimbabwe	0.10

Notes: * statistically significant at 10 percent level.

Table 4.5: Pair-wise correlation estimates between IAR4Dness, Principles and baseline characteristics

	IAR4Dness	Principle 1	Principle 2	Principle 3	Principle 4	Principle 5
Household characteristics						
Gender	0.18	0.17	0.08	0.24	-0.48*	0.14
Age	0.23	0.28	0.27	0.19	0.05	0.20
Education	0.12	0.11	0.03	0.27	0.33*	0.16
Size	0.04	0.18	0.22	0.38*	0.16	0.06
Village Amenities						
School	0.21	0.01	0.01	0.12	0.38*	0.10
Hospital	0.33*	0.05	0.08	0.07	0.52*	0.04
Worship	0.24	0.15	0.10	0.04	0.33*	0.07
Socialhall	0.09	0.05	0.03	0.16	0.20	0.24
Roads	0.24	-0.45*	-0.47*	0.34*	0.25	0.13
Mobile network	0.09	0.01	0.09	0.24	0.17	0.10
Village social capital						
Participation	0.09	0.29	0.22	0.25	0.25	0.18
Trust	0.06	0.20	0.16	0.27	0.39*	0.14
Cooperation	0.10	0.15	0.10	0.25	0.41*	0.23
Gift exchange	0.05	0.27	0.16	-0.32*	0.39*	0.04
Contrcomm	0.28	-0.43*	-0.35*	0.21	0.08	0.09
Contributgr	0.29	-0.54*	-0.42*	0.26	0.17	0.03
Helping	0.12	-0.42*	-0.35*	0.16	0.39	0.23
Conflicts	0.05	0.17	0.09	-0.32*	0.05	0.19
Norms	0.30	-0.54*	-0.52*	0.17	0.24	0.05
Women confid.	0.06	0.15	0.15	0.00	0.05	0.17
Consd. women	0.02	0.08	0.06	0.20	0.02	0.17
Regions						
DRC	0.41*	0.58*	0.57*	-0.29	-0.14	0.31*
Malawi	0.03	0.06	0.06	-0.01	-0.04	0.03
Mozambique	0.19	0.18	0.19	0.19	0.01	0.01
Northern Guinea Savanna (Nigeria)	-0.42*	-0.22	-0.42*	0.47*	-0.12	-0.62*
Rwanda	-0.29	-0.38*	-0.35*	0.12	-0.10	-0.05
Sudan Savannah (Nigeria and Niger)	0.36*	-0.17	0.05	-0.39*	0.70*	0.49*
Sahel (Nigeria)	0.04	0.21	0.09	0.03	-0.22	0.04
Uganda	-0.08	-0.11	-0.03	-0.19	0.13	-0.06
Zimbabwe	-0.31*	-0.15	-0.18	0.13	-0.30*	-0.21

Notes: * statistically significant at 10 percent level.

Do baseline characteristics affect the quality of project implementation? If the answer to this question is “Yes”, the quality of project implementation may not be exogenous to baseline IP characteristics. We again answer this question by estimating pair-wise correlation coefficients between baseline household and village characteristics as well as region dummies at IP level and IAR4Dness index. Table 4.5 presents the estimates. Results indicate there is a correlation between most of the IAR4Dness principles and baseline characteristics, and implementation quality differs in the regions. This may reflect the fact that the performance of IPs is correlated with the development level of and social cohesion in the villages surrounding IPs. As some of those factors are also correlated with our outcome variables (see Table 4.4 above,) we will design our identification strategy accordingly to estimate the impact of IAR4Dness on food security (see below for details).

4.6 IAR4Dness and FCS

4.6.1 Identification strategy

We now summarize the identification strategy that we use to investigate the effect of IAR4Dness on outcome variables. To control for the potentially confounding effect of household, village and IP level characteristics on our outcome variable and IAR4Dness, we use data from the baseline survey conducted in 2008 and the midline survey conducted in 2010/2011, and define our outcome variables at the household level whereas our IAR4Dness variables are defined at IP level. We also use clustered robust standard errors at the IP level for the estimations to control for within IP correlation of error terms.

If the IAR4Dness was random across IPs, we could estimate the following model, for outcome variable Y_{iprt} and test the hypothesis that $\alpha_2 \neq 0$:

(4.1) $$Y_{iprt} = \alpha_0 + \alpha_1 T_t + \alpha_2 I_{pt} + R_r + R_r T_t + \gamma_p + \gamma_p T_t + u_{iprt}$$

where subscripts *i, p, r* and *t* denote household, IP, region and period respectively. I_{pt} represents our main variable of interest, the IAR4Dness indices, and equals zero for the baseline period because IAR4D was introduced after the baseline period. We use rescaled values for indices identified in Table 4.3 (and Table 4.1 when necessary) having a mean of zero and a standard deviation of one to ease the interpretation of the estimates. T_t is a dummy variable, equals to 1 for midline survey, and controls for the general trend between two survey periods. R_r is a region fixed effect, $R_r T_t$ is region trend, γ_p is IP fixed effect, and $\gamma_p T_t$ is a IP level trend. u_{ivprt} is the random error term. To eliminate the IP and region level fixed effects, we use balanced sample of households and write (4.1) in first differences:[42]

$$\Delta Y_{iprt} = Y_{ipr,t} - Y_{ipr,t-1} = \alpha_1 + \alpha_2 I_p + R_r + \varepsilon_{iprt} \tag{4.2}$$

where $(\gamma_p + \Delta u_{iprt}) = \varepsilon_{iprt}$ is the error term in our regression. To control for R_r, we use region level dummy variables in the estimations.[43] We also add baseline household and village characteristics to the estimations to control for γ_p.[44] If there is any correlation between I_p and γ_p, we assume that this is controlled for through the control variables used in our main specifications. In robustness checks (see below), we will relax this assumption by using an instrumental variable strategy, and test the robustness of our results.

We start our analysis by estimating (4.2) for the overall index. Then, to explore through which principles and factors the impact of the index is driven, we refine our results by estimating (4.2) for each principle and factor separately.[45] Separate estimation of the models prevents the inflation of standard errors in the estimations as some of the IAR4Dness principles are highly correlated (see appendix 3 for details). These correlations between the principles result from the definition and the construction of the variables (see section 4.3).

4.6.2 Baseline estimation results for food security

The estimation results of model (4.2) for our main outcome variable, FCS, are summarized in Table 4.6. We report the estimates for our coefficients of interest: average IAR4Dness, principles and factors at each column. We control for household and village characteristics as well as region fixed effects in all regressions. The results show that FCS levels are

[42] In the main estimations, we use 31 IPs instead of 32 since we cannot identify the households balanced household for an IP due to missing household identifier variables in the dataset. However, our results are robust to using unbalanced sample and an alternative specification to first difference where we control for IP level fixed and region trends. The results are available upon request.
[43] In the data, there is substantial heterogeneity at region level, and therefore our estimation results are sensitive to adding region level dummy variables. Our estimates are not statistically significant if we do not control for them.
[44] We do not control for the village characteristic in panel D of Table 2 in our main estimation results because they were only collected in 28 IPs in baseline surveys. However, our main results are robust to estimating our models for only 28 IPs and controlling for these village level social capital variables.
[45] Our results are robust to the inclusion of the two factor variables in one model.

higher in the villages where the level of IAR4Dness is higher. One standard deviation in IAR4Dness index increases the FCS by 6.42. To explore which principles matter most, we repeat model (4.2) for each principle in columns (2-6). The relation between IAR4Dness and FCS mainly stems from two IAR4Dness principles: non-linear, collective and collaborative interaction (principle 2) and institutional and human capacity building for IP actors (principle 5). These results are in line with the results shown in column 7 and 8. IPs with active participation to the activities, factor 1, have higher levels of FCS. However, not depending on whether the main explanatory variable is statistically significant estimated R^2 do not vary between models. This implies that most of the variation in FCS is explained by region dummies, and IAR4Dness and Principles explain a small part of the variation. This limits the interpretation of our analysis.

Table 4.6: Regression estimates for IAR4Dness and food security

Dependent variable:	ΔFCS	ΔFCS	ΔFCS	ΔFCS	ΔFCS	ΔFCS	ΔFCS	ΔFCS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IAR4Dness	6.42***							
	(1.51)							
Principle 1		1.44						
		(1.64)						
Principle 2			3.41*					
			(1.68)					
Principle 3				2.56				
				(3.16)				
Principle 4					1.10			
					(2.29)			
Principle 5						5.18**		
						(2.09)		
Factor 1							4.94***	
							(1.43)	
Factor 2								-0.22
								(1.66)
Constant	25.30***	16.11**	17.66***	14.96**	17.46**	23.04***	23.27***	15.79**
	(6.19)	(6.27)	(6.23)	(6.43)	(8.22)	(6.89)	(6.72)	(6.37)
Observations	1335	1335	1335	1335	1335	1335	1335	1335
R-squared	0.16	0.14	0.15	0.15	0.14	0.16	0.16	0.14

Notes: * p<0.10, ** p<0.05, *** p<0.01, Robust standard errors clustered at IP level are in the parentheses. All regressions include regional dummy variables. We present estimates for the variables of interest to economize on space

To explore the key factors behind our main result we next explore the correlation between FCS and the sub indicators concerning involvement in IP activities: Principle2a, Principle 2b, Principle 4a and Principle 5. We predict that related sub-components of the indices might be the key factors behind the positive correlation between FCS and the principles. To test whether our conjecture is true, we estimate (4.2) for four additional specifications. We replace I_p with the average involvement in listed activities (Principle 2a), difference in average participation (Principle 2b), average involvement in planning and joint implementation (Principle 4a) and average involvement in information sharing activities and field visits (Principle 5) (see Table 4.7).

Table 4.7: Involvement indicators and food security

Dependent variable:	ΔFCS (1)	ΔFCS (2)	ΔFCS (3)	ΔFCS (4)
Principle 2a	5.37***			
	(1.50)			
Principle 2b		-0.54		
		(1.58)		
Principle 4a			3.31*	
			(1.69)	
Principle 5				5.18**
				(2.09)
Constant	23.95***	15.99**	20.08***	23.04***
	(6.68)	(6.51)	(7.16)	(6.89)
Observations	1335	1335	1335	1335
R-squared	0.16	0.14	0.15	0.16

Notes: * p<0.10, ** p<0.05, *** p<0.01, Robust standard errors clustered at IP level are in the parentheses. All regressions include regional dummy variables. We present estimates for the variables of interest to economize on space.

The results in Table 4.7 confirm our conjecture that average participation in the activities is positive and significantly correlated with FCS. Moreover, the type of activities seems to be key in improving food security. Participation in information sharing activities and field visits is more important than participation in activities concerning joint planning and implementation as the estimates are bigger and statistically more significant for the former. Finally, equal participation of stakeholders to these activities does not seem to be a critical factor for our results.

4.6.3 Robustness checks

Our identification strategy rests on two assumptions. First, clustering standard errors at the IP level gives correct estimates for standard errors. Second, the level of IAR4Dness is not correlated with IP level time trends that may also influence our outcome variables. In this section, we relax these assumptions and test the consistency of our estimates. In Tables 4.8 and 4.9, we report the estimates from alternative models specified to test the robustness of our main results. We focus on the impact of Principle 2a, Principle 4a and Principle 5 on FCS because we found that our results are mainly driven by attendance to IP activities.

Table 4.8: IP level estimates

	IP level estimates		
Dependent variable:	ΔFCS	ΔFCS	ΔFCS
	(1)	(2)	(3)
Principle 2a	6.12**		
	(2.59)		
Principle 4a		2.24	
		(2.98)	
Principle 5			6.60*
			(3.41)
Constant	17.22***	13.51**	16.36**
	(6.05)	(6.34)	(6.11)
Observations	32	32	32
R-squared	0.46	0.41	0.47

Notes: * p<0.10, ** p<0.05, *** p<0.01, Robust standard errors clustered at IP level are in the parentheses. All regressions include regional dummy variables. We present estimates for the variables of interest to economize on space.

As a first robustness test we re-estimate model (4.2) at IP level. Although the standard errors of our main model are clustered at the IP level, household level analysis still might produce low standard errors, and overstate the significance of our estimates because IAR4Dness is measured at the IP level (Wooldridge, 2003). For this analysis, we use the difference of IP level average of FCS as the dependent variable, and drop household and village level controls. Columns 1, 2 and 3 of Table 4.8 show that estimates for *Principle 2a* and *Principle5* are statistically significant and are in line with our previous estimates but the estimate for *Principle4a* is not statistically significant.

As a second robustness analysis, we estimate a 2SLS model to isolate the potential impact of unobserved time varying determinants at IP level. Unobserved factors such as economic and income shocks that happened after the baseline period may have directly affected both FCS and IAR4Dness. This might create an endogeneity problem for our estimates. To address this concern, we employ exogenous variation in the duration of field activities of IPs as an instrument (see Panel E in Table 4.3 for variable descriptions). Some IPs started their field operations later than others due to organisational challenges. Hence, (more) mature IPs had more opportunity to organize IAR4Dness activities. Besides, to our knowledge, the start-ups of IPs were not delayed by IP level shocks; therefore we argue that the duration is not correlated with other unobserved factors time varying factors. However, having more time to adopt and use the proposed technologies households can benefit more from the intervention and have higher food consumption levels; therefore a direct effect of the duration of exposure to the IAR4Dness program on FCS may exist and a reason of concern for the validity of the instrument. To circumvent this concern, before presenting the 2SLS estimates below, we will first conduct a weak exogeneity test for the instrument by inserting it to the IP level estimations, together with the main explanatory variables. If the duration of field activities has a direct impact (not an indirect impact only through the Principles) on FCS, the coefficient estimates for the instrument will not be statistically significant in those estimations.

The specification of 2SLS model employed is as follows. The following is the first stage equation via which we predict the *Principle2a, Principle4a* and *Principle5*:

$$I_p = \beta_1 + \beta_2 D_p + R_r + \varepsilon_{prt} \tag{4.3}$$

where R_r is region fixed effect and ε_{prt} refers to error term. D_p denotes our excluded instrument which equals 0 in baseline survey period as there is no field activity and 1 when years of field activities for corresponding IP is more than 1.5 years (median level) in midline survey period.[46] Again, we control for region fixed effects by adding region dummy variables into our models. We justify the use of the same IV for both principles because they both relate to attendance (in fact Principle5 and Principle4a are sub elements of Principle 2a), and years of field activities should explain both. As our instrument is at the IP level, the predicted values for I_p from (4.3) are used again to estimate (4.2) at IP level for Principle2a, Principle4a and Principle5 by using 2SLS estimation.

[46] We use dummy variable as instrument to increase the precision of the estimates. When we use actual years of field activities but not dummy variable as the instrument, then our coefficient estimates are very close but imprecise and thereby not statistically significant.

Table 4.9: First stage estimates, exogeneity checks and 2SLS estimates

	Exogeneity checks			First stage estimates			2SLS		
Dependent variable:	ΔFCS	ΔFCS	ΔFCS	Principle 2a	Principle 4a	Principle 5	ΔFCS	ΔFCS	ΔFCS
	(4)	(5)	(6)	(1)	(2)	(3)	(7)	(8)	(9)
Principle 2a	5.25**						20.43		
	(2.44)						(12.87)		
Principle 4a		2.51						-64.03	
		(2.84)						(189.38)	
Principle 5			5.59						12.91*
			(3.40)						(7.44)
Years in field (dummy)	7.65	10.71	5.84	0.50*	-0.16	0.80**			
	(6.83)	(6.73)	(6.70)	(0.28)	(0.55)	(0.30)			
F-stat for the instruments							3.29	0.89	7.31
Observations	32	32	32	32	32	32	32	32	32
R-squared	0.48	0.45	0.49	0.71	0.57	0.72	0.14	-9.32	0.41

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$, Robust standard errors clustered at IP level are in the parentheses. All regressions include regional dummy variables. We present estimates for the variables of interest to economize on space.

Before presenting the 2SLS estimates, we also assess how relevant the endogeneity concerns are by using Durbin-Wu-Hausman test proposed by Davidson and Mckinnon (1993). Test results show that we cannot reject the null hypothesis - there are no endogeneity in the estimates for the Principle 2a, 4a and 5 at 27, 12, and 39 percent significance levels. Hence the concerns regarding endogeneity of our main explanatory variables, in particular for Principle 5, should be limited. Yet we provide the results for the exogeneity tests, first stage estimation results, and 2SLS estimates in Table 4.9. Columns 1, 2, and 3 show the estimation results for the exogeneity tests where D_p added as an additional explanatory variable to the original models presented in Table 4.8. The coefficient estimates for the duration of field activities are insignificant in the estimations; it is therefore not correlated to FCS directly (only through the Principles) and satisfies the exclusion restriction. Columns 4, 5 and 6 report the first stage estimates for Principle2a, Principle4a and Principle5 respectively. A longer period of field activities enhances the information sharing activities and field visits but not average involvement in other activities (F-statistics for Principle 5 equals 7.31). Finally, columns 7, 8 and 9 present the 2SLS estimates for Principle2a, Principle4a and Principle5 respectively. The estimates are positive and statistically significant for only Principle 5. Hence, results confirm that our estimates for only Principle 5 is consistent when we isolate the impact of unobserved time varying factors using years of field activities as an instrument.

To summarize, the results imply that the IPs that have been more successful in enhancing participation in information sharing and field activities may perform better in improving food consumption at region level. For instance Gataraga and Bufindi from Lake Kivu are among the IPs having highest participation rate to the activities, and Chapter 2 has shown that they have performed better than IPs located at the same countries in enhancing FCS. Hence our results also shed some light on the heterogeneity within each region in terms of the program impact on FCS, but do not completely explain the source of the heterogeneity.

4.7 Examining the mechanism: Impact of Participation to Field Activities on Intermediate Outcomes

How does participation in information sharing and field activities (Principle 5) increase food security? To probe this question, we tentatively investigate the effect of Principle 5 on three sets of intermediate outcome variables: agricultural technology, marketing strategies, and social capital variables (see section 4.3.3 for variable details). We use the 20 intermediate outcome variables introduced in Table A.4.3, and estimate (4.2) for each of them separately. To economize on space we do not report these estimates, but they are available upon request.

We find mixed results concerning the impact of Principle 5 on intermediate outcome variables. Households seem to change their preferences for agricultural technology adoption in IPs with more participation in field activities. First, estimates show that increased participation in field activities promotes the adoption of two agricultural technologies: adoption of mulching and chemical fertilizer usage. However, it is negatively correlated with the adoption of animal manure and three post-harvest technologies – threshing and shelling equipment, storage facilities and pest control. Second, households change where they market their products as a result of information sharing and field activities. Estimates for marketing strategies indicate that households in "high Principle 5 IPs" are less likely to sell their products on-farm to consumers and or local/village market in the villages. Finally it appears that field activities did not promote interaction of household with others, as Principle 5 is not significantly correlated with any social capital variables at household level.

Because Principle 5 is positively related with only mulching and chemical fertilizer usage, we tentatively test whether Principle 5 leads to an increase in food security through the adoption of those technologies. To do this, we estimate two new specifications of (4.2) in which we respectively use changes in the adoption of mulching and chemical fertilizer as explanatory variables (in addition to Principle 5). If the impact of Principle 5 on FCS stems from adoption of those technologies, adding those technology variables to the specifications should result in smaller coefficient estimates for Principle 5, and technology variables will be significantly correlated with FCS. Also we note that we cannot use the estimate for Principle 5 reported in Table 4.5 to compare with our new estimates, because samples used for the new estimations are smaller due to missing values for the technology variables. Therefore we obtain two new benchmark estimates for Principle 5 for comparison by estimating (4.2) for Principle 5 by using the households for which observations for change in mulching and chemical fertilizer usage are not missing respectively.

Table 4.10: Test for mechanism

Dependent variables:	ΔFCS (1)	ΔFCS (2)	ΔFCS (3)	ΔFCS (4)
Principle5	5.53***	5.54***	6.40***	6.35***
	(1.80)	(1.77)	(1.89)	(1.86)
ΔMulching		-0.17		
		(1.45)		
ΔChemical Fertilizer				0.99
				(2.10)
Constant	18.51***	18.59***	24.15***	23.82***
	(6.33)	(6.31)	(7.45)	(7.39)
Observations	1,054	1,054	1,188	1,188
R-squared	0.13	0.13	0.13	0.13

Notes: * p<0.10, ** p<0.05, *** p<0.01, Robust standard errors clustered at IP level are in the parentheses. All regressions include regional dummy variables. We present estimates for the variables of interest to economize on space.

Table 4.10 reports the results for the impact Principle 5 and change in the adoption of mulching and chemical fertilizer on FCS. Estimates for Principle 5 in column 1 and 3 serve as the new benchmarks for the estimates in column 2 and 4 respectively. Results show that the increase in the adoption of these technologies did not cause the increase in food security since the estimates for the change in technology usage are not statistically significant, and the estimate for Principle 5 in column 2 and 4 are not smaller than the ones in column 1 and 3 respectively. These results may imply that adoption of technologies by itself may not improve food security, and should be supported by other policies which we do not observe and identify here.

Several caveats are relevant. First, the power of our estimates for technology variables is low as we observe only 32 IPs. So we may fail to reject a false hypothesis and may not identify a potential mechanism. Second, our intermediate outcome variables are far from perfect as we do not observe the intensive margin for them. For instance households may produce and sell more agricultural goods in high Principle 5 IPs. However, our intermediate outcome variables cannot capture such changes as they are binary variables. Third, the list of intermediate outcome variables may be incomplete as we do not have information concerning intermediate outcomes such as improved variety usage, employment levels and access to finance of households which may directly affect food security. Last but not least it may be difficult to detect the exact mechanism due to decentralized policy design and implementation processes of IPs. In the decentralized innovation systems, each IP focuses on a different technology or marketing strategy, reflecting needs and opportunities of the villages.

4.8 Conclusion

There is considerable heterogeneity in the impact of the innovation system approach on resource poor farmers at IP level. In this study, we argued this may be because there is heterogeneity in implementation: IPs may not have equally implemented the principles of the IAR4D approach. We explore heterogeneity in implementation, and the effect thereof, by quantifying the five defining principles of IAR4D into an IAR4Dness index and linking these to the main survey data. We find that the IAR4Dness index is correlated positively and significantly to FCS, our proxy for food security.

This relation between IAR4Dness and FCS mainly stems from an IAR4D sub principle: institutional and human capacity building for IP actors (principle 5). Looking at the sub-components of the principle, especially participation in information sharing activities and field visits is crucial. Success of IPs thus seems to depend on the attendance and contributions of stakeholders to the activities of the IPs; Thus IPs which are better at making stakeholders participate to those meetings than other IPs at the same regions have higher food consumption levels than those IPs. Yet we cannot argue that this factor is the only reason among the heterogeneity between IPs, as the level of participation to information sharing and field activities explain only a small part of the variation in the FCS between IPs.

More specially, we believe this result may indicate that IPs only become beneficial for villagers when they (and other IP stakeholders) participate in capacity building events such as field visits and information sharing activities. Recent case study evidence from improved maize legume and production systems in Nigeria supports our findings, and explains how capacity building activities help the platform perform. Dangbegnin et al. (2011) state that the platform organised capacity building activities on IAR4D and team building to enhance problem solving, team working and learning skills of platform members. They argue that these activities “enabled platform members to work as equal partners” (p. 92).

It is also interesting to note that other IAR4Dness (sub) indicators of IAR4D do not seem to matter in terms of impact on FCS. For example, the different types of stakeholders involved or equal participation of these stakeholders to activities. Apparently average participation is more important than diversity per se. In fact it is easy to imagine some sort of trade-off between the number of stakeholders involved in an IP and the average participation of these stakeholders. This was supported by our factor analysis. It could well be that this means that IPs with less diverse partnerships, but overall higher average participation because of this, are more successful than IPs with many additional but low participating partners. Perhaps it becomes more difficult to manage the IP as it becomes bigger: i.e. it might be harder to align different goals and objectives and coordinate the IP.

We also find that the effect of IAR4Dness on FCS does not operate through increased use of agricultural technologies, increased use of different marketing strategies or increased levels of household social capital. However, we only investigate three potential channels through which IPs can boost FCS. There are many other potential channels such as improved variety or access to finance. There is need for future research to shed light on these channels.

Finally, we note three methodological issues regarding our results. First of all, we show that researchers can investigate the heterogeneity in the implementation of a project and the performance of the project partners by applying a survey to the partners after the treatment. However, we are aware of the fact that our IAR4Dness measures might be subject to measurement errors as we utilize a set of objective questions directed to platform members after two to three years implementation of the project. To minimize the error, a better approach might be collecting data from all stakeholders through a consistent monitoring and evaluation (M&E) survey during implementation. Secondly, we use data from baseline and midline surveys conducted merely two to three years after the platforms are established. This means that our results reflect only the short-term effects of IAR4Dness from early maturing platforms. An end-line survey is scheduled for late 2014. By using the new data set from matured platforms, follow up research should probe the robustness and sustainability of the preliminary results presented here. Finally, we observe limited number of IPs; hence consistency of our estimates may be questionable. Future work should investigate whether the results we reach are consistent by using additional data to be collected in the future.

4.A Appendices

Appendix: Project learning sites, countries, implementing agents and IPs

West Africa (KKM): Niger and Nigeria

- INRAN: IPs related to livestock-feed, millet-cowpea, vegetables, and groundnut.
- IFDC: IPs related to livestock-feed, maize-legume-livestock, vegetables, and rice
- IITA: IP related to maize-cowpea-livestock, and 2 related to sorghum-cowpea-livestock

East Africa (LK): DRC, Rwanda and Uganda

- CIAT: IPs related to banana, Irish potatoes, beans and cassava
- ISAR: IPs related to NRM, livestock, milk, seed potato and maize
- Makerere/ICRISAT: IPs related to potato, soil and water conservation, pineapple and sorghum

Southern Africa (ZMM): Zimbabwe, Malawi, Mozambique

- CIAT: IPs related to conservation agriculture
- Bioversity International: IPs related to horticulture

Appendix: Characterization of IAR4D as implemented by FARA

Please note this is a modified version of the actual 2.5 page survey. All data collected is listed, but to economize space, the structure has been revised. The text in italic between brackets refers to pre-defined answer categories.

<u>Identification IP</u>

Name of the organisation; Name of the Innovation Platform (IP); Country of the IP; District of the IP; Sub country/other of the IP; When was the IP formed (month and year).

<u>Identification respondent</u>

Your Name; E-mail address; Your position in the organisation; Your role in the IP.

<u>IP formation and functioning</u>

How did the IP originate? (*from scratch, builds on existing networks, already fully existed)*
How is the IP facilitated? (*researchers, by local stakeholders, jointly)*
How are participants selected for the IP?

IP participation of stakeholder

Which of these stakeholders are represented in the IP? *(yes, no - see footnote* 41 *for list of stakeholder)*
How often (approximately) do the following partners in your IP conduct or attend a) joint planning of activities; b) joint implementation of activities; c) information sharing; d) field visits or workshops; e) seminars and training events? (*daily, weekly, monthly, every six month, every year or less)*

Problems addressed

Is the problem area addressed in IP? *(yes, no)* a) low agricultural technology use; b) access to inputs; c) market access and strategy problems; d) land related problems; e) other.
Who identified the problem *(list of stakeholders in footnote 41)*
Was the problem prioritized *(yes, no)*
Was an action implemented *(yes, no)*
Who designed the policy *(list of stakeholders in footnote 41)*
What is the action?

Appendix: Additional tables

Table A.4.1: Factor analysis IAR4Dness indices (n=32)

Variable	**Factor1**	**Factor2**
Principle 1		0.9428
Principle 2a	0.993	
Principle 2b		0.968
Principle 3a	-0.512	
Principle 3b*		
Principle 4a	0.831	
Principle 4b		-0.438
Principle 5	0.927	

Note 1: blank spaces are loading < .4

*excluded because the same (1) for all IPs

Table A.4.2: Correlation coefficient estimates for IAR4Dness index and principles (n=32)

	IAR4Dness	Principle 1	Principle 2	Principle 3	Principle 4	Principle 5
IAR4Dness	1					
Principle 1	0.65*	1				
Principle 2	0.85*	0.91*	1			
Principle 3	-0.40*	-0.41*	-0.55	1		
Principle 4	0.52*	-0.17	0.07	-0.15	1	
Principle 5	0.80*	0.36*	0.66*	-0.6	0.41*	1

Note: * significant at least 10 percent level

Table A.4.3: Summary statistics for intermediate outcomes

		Obs	Mean	Std. Dev.
Mulching	equals 1 if a household uses mulching , 0 otherwise	3129	0.32	0.47
Trenches/terraces	equals 1 if a household uses trenches/terraces, 0 otherwise	3070	0.29	0.45
Water harvesting	equals 1 if a household uses water harvesting, 0 otherwise	2754	0.17	0.38
Irrigation	equals 1 if a household uses irrigation techniques, 0 otherwise	3090	0.27	0.44
Conservation farming	equals 1 if a household uses conservation farming, 0 otherwise	2892	0.24	0.43
Animal manure	equals 1 if a household uses animal manure 0 otherwise	3260	0.69	0.46
Cover crops	equals 1 if a household uses cover crops, 0 otherwise	2803	0.29	0.45
Crop rotation	equals 1 if a household uses crop rotation, 0 otherwise	3085	0.60	0.49
Inter cropping	equals 1 if a household uses inter cropping, 0 otherwise	2609	0.56	0.50
Rhizobiainoculation	equals 1 if a household uses Rhizobiainoculation , 0 otherwise	2502	0.03	0.17
Chemical fertilizer	equals 1 if a household uses chemical fertilizer , 0 otherwise	3259	0.55	0.50
Row planting	equals 1 if a household uses row planting , 0 otherwise	3067	0.67	0.47
Plant spacing	equals 1 if a household uses plant spacing, 0 otherwise	2988	0.58	0.49
Organic pesticide	equals 1 if a household uses organic pesticide, 0 otherwise	3029	0.25	0.44
Inorganic pesticide	equals 1 if a household uses inorganic pesticide, 0 otherwise	3115	0.48	0.50
Drying	equals 1 if a household uses drying, 0 otherwise	3137	0.75	0.43
Threshing/shelling	equals 1 if a household uses threshing shelling equipment, 0 otherwise	3104	0.47	0.50
Improved storage facil.	equals 1 if a household uses improved storage facilities, 0 otherwise	3062	0.24	0.43
Pest control	equals 1 if a household uses pest control, 0 otherwise	3142	0.47	0.50
Grading	equals 1 if a household uses grading, 0 otherwise	2957	0.47	0.50

Table A.4.3 (continued): Summary statistics for intermediate outcomes

		Obs	Mean	Std. Dev.
Marketing Strategies				
Consumers	equals 1 if household sold at least one type of product on farm to consumers, 0 otherwise	2861	0.24	0.42
Middleman	equals 1 if household sold at least one type of product on farm to middleman, 0 otherwise	2861	0.17	0.37
On the roadside	equals 1 if household sold at least one type of product on the road side, 0 otherwise	2861	0.09	0.28
Local market	equals 1 if household sold at least one type of product at the local/village market, 0 otherwise	2861	0.36	0.48
District town	equals 1 if household sold at least one type of product at the district town market, 0 otherwise	2861	0.17	0.37
Distant market	equals 1 if household sold at least one type of product at a distant market, 0 otherwise	2861	0.16	0.37
Household level social capital				
Development Projects	Equals 1 if household participated in community development projects, 0 otherwise	2968	0.81	0.40
Collective problem	Equals 1 if household financially contributed to community activities or collective problems, 0 otherwise	2883	0.74	0.44
Conflict	Equals 1 if household involved in settling conflicts or disputes among people, 0 otherwise	2835	0.69	0.46
Visit within farmers	Equals 1 if household visited other farmers within community to learn about agriculture, 0 otherwise	2809	0.57	0.50
Visit outside farmers	Equals 1 if household visited other farmers outside community to learn about agriculture, 0 otherwise	2738	0.38	0.49
Visit research station	Equals 1 if household visited a research station to learn about agriculture, 0 otherwise	2691	0.21	0.40
Visit extension office	Equals 1 if household visited an extension office to learn about agriculture, 0 otherwise	2699	0.26	0.44

Chapter 5

Market integration and the evolution of trust: Evidence from West Africa*

5.1 Introduction

Economic analyses have revealed a positive correlation between trust levels and economic performance (e.g. Knack & Keefer, 1997). Trust lowers transaction costs, which facilitates trade and invites static and dynamic efficiency gains. "Virtually every commercial transaction has within itself an element of trust, certainly any transaction conducted over a period of time. It can be plausibly argued that much of the economic backwardness in the world can be explained by the lack of mutual confidence" (Arrow, 1972: 357). For trade to flourish and extend beyond "flea market" barter or cash-and-carry modes of exchange, moral obligations of fairness and reciprocity should extend to anonymous others. While fairness and reciprocity norms extending to kith and kin may regulate exchange in traditional societies based on self-provision, generalized morality and trust should develop and spread for broader (and more beneficial) patterns of trade to take off (Platteau 1994; Fafchamps 2011; Tu & Bulte 2011). In light of this observation it is no surprise that searching for the determinants of trust has emerged as an important research topic in the social sciences.

The role of market integration as a determinant (rather than a result) of trust, fairness and reciprocity has received some attention in recent years (e.g., Tabellini 2008, Henrich et al. 2010; Siziba & Bulte, 2012). The breadth and intensity of market exchange

* This Chapter is based on following research paper: Pamuk, H., Bulte, E., & van Soest, D. (2014). *Market Integration and the Evolution of Trust: Evidence from West Africa*. Unpublished manuscript

varies across societies, and has varied over time within societies. The transition from subsistence farming and local, personalised exchange to specialisation and long-distance, impersonal exchange is widely regarded as an essential component of overall economic development (e.g. Fafchamps 2011). This process of market integration implies important changes in the social structure of societies. For example, Kumar and Matsusaka (2009) emphasize the difference between "village social capital" and "market social capital." Village social capital typifies rural economies in poor countries, and takes the form of kinship ties, patron-client relations, and repeated personalised exchange. In contrast, market social capital involves access to and knowledge about third-party punishment, including courts, auditors, credit ratings, and so on. To reap the potential benefits from specialisation and trade, communities should adjust the composition of their (structural) social capital stocks—divesting in village capital and investing in market capital.[47]

However, the implications of broader and deeper integration into markets may be more fundamental than this, and extend to the *cognitive* domain of social capital as well – affecting levels of trust and trustworthiness in society. Using an RCT design, Al-Ubaydli et al. (2013) find that 'priming' experiment participants for market participation positively affects expectations about the trustworthiness of others, and increases amounts sent in a trust game. Supporting this evidence, Buchan et al. (2012) show that individual and country level indexes of connectedness to global economic and social networks are positively related to cooperation with strangers, which is measured by the money shared with groups from different countries, in a multilevel sequential cooperation experiment conducted in 7 different countries. Based on an extensive study that involved the collection of experimental data across various societies, Henrich et al. (2010) propose that "market norms may have evolved as part of an overall process of societal evolution to sustain mutually beneficial exchanges in contexts where established social relations (for example, kin, reciprocity, status) were insufficient" (p.1480). Hence, market integration "involved the selective spread of those norms and institutions that best facilitated successful exchange…" (p.1484). If so, market integration speaks to the puzzle of the origins of

[47] Theoretical models have probed such investment trajectories and emphasized that the desired transformation may not occur in the presence of strategic complementarities (e.g., Kranton, 1996; Kumar & Matsusaka 2009). If so, a poverty trap might eventuate.

human prosociality. Behavioral evidence and observational data suggest most people display fair, trusting and cooperative behaviour – even with strangers and in one-shot encounters. Such behavior is arguably supported by norms of fairness and trust, sustained by internalization, punishment, or signalling and reputation effects—begging the question about the origins and evolution of such norms. If market integration fosters trust through spreading these norms and if trust, in turn, promotes market integration, then trade and trust are *complements* in development. Supporting this important thesis, Henrich et al. (2004, 2010) document a strong and robust positive correlation between experimental measures of trust and fairness on the one hand, and an objective measure of market integration on the other hand.

The final word about the complex inter-relationship between trust and trade, however, remains to be written. The evidence provided by Henrich et al. (2004, 2010) is based on cross-sectional data collected in 15 societies. The sample of societies included in this study is (intentionally) diverse, implying that the risk of omitted variables looms large. Correlation between trust and market integration thus need not imply any *causal* relationship between these variables. Cross-section studies may also gloss over potentially considerable intra-regional heterogeneity of various relevant variables, which renders interpretation difficult and may produce biased estimation results (Imbens & Angrist, 1994).

In addition, related theories also imply that the relationship between market integration and trust may be more complex than the story Henrich et al. (2004, 2010) propose. For instance, in his seminal model, Tabellini (2008) shows that increased trade may let generalized morals spread in society through generations. Without formal regulations enforcing trade contracts, generalized trust can secure cooperation between socially distant agents; therefore parents may prefer transmitting general morals to their children so that new generations can benefit from distant trade. Acemoglu and Wolitzky (2012) however suggest that the relationship might be negative as well. They show phases of distrust between trading parties may occur in repeated interaction between traders from different groups (i.e. societies, communities) due to the combination of imperfect information between trading partners and product quality problems. Hence, the relationship between trust and trade may be negative as well as positive.

For these reasons it seems prudent to complement the above analyses by probing the relation between market integration and trust using data from a large and culturally relatively homogenous sample of households in Northern Nigeria and Niger (see below). We seek to extend the pioneering work of Henrich et al. (2004, 2010) by moving beyond correlations to establish the causal effect of market integration on trust. We identify *exogenous variation* in market integration, and use a system's approach to statistically analyse how trade affects trust. Insight in this particular causal effect allows us to evaluate the hypothesis that market integration and trust are complements—mutually reinforcing each other in a co-evolutionary process of (economic) development. From a normative (or policy) perspective, this is relevant information. If trade and trust are complements in development, a short-term exogenous "shock" or policy intervention could place autarchic societies on a self-propelling trajectory of increasing trust and market integration. From a positive perspective, this raises the question why not all communities are characterized by high trust and high market integration.

The objective of this Chapter is to analyse the causal effect of market integration on various survey-based measures of trust in a society at an early level of economic development and characterized by relatively low levels of trade. We distinguish between trust in fellow villagers (*personalized* trust) and trust in strangers (*generalized* trust), and are especially interested in assessing whether market integration fosters trust in strangers. Our main result is that trade does *not* invite such trust—the opposite appears true for our sample of African villagers. We typically find that, if anything, higher levels of market integration reduce the various types of trust, although this causal effect is only statistically significant in communities with below-average quality institutions. Hence, increased market integration does not necessarily put villages on a path to economic prosperity—formal institutions play an important mediating role. We speculate this may explain the persistence of low levels of market integration and trust in large pockets of the developing world.

This paper is organized as follows. In section 5.2 we introduce our data and outline our identification strategy. Section 5.3 contains our results – extensive series of OLS, probit, and 2SLS estimates. We also present some preliminary and tentative results sketching the mechanism linking market integration to trust. In section 5.4 we discuss our main findings, placing them into the wider context of trade and trust, and draw some conclusions.

5.2 Data

We use data collected in Northern Nigeria and Niger (the "Kano-Katsina-Maradi region") as part of the so-called Sub-Saharan African Challenge Program (see FARA 2009 for details).[48] Ten households per village were sampled in 180 villages. Survey data were collected during two waves: a first wave in 2008, which included detailed data about expenditures (allowing us to construct household-level proxies of market integration), and a second wave in 2010, which included several questions about personalized and generalized trust. There are no trust data for 2008, and no detailed expenditure data for 2010, so there is no scope for a full-fledged panel analysis. Instead, we will merge the 2008 and 2010 waves to construct one cross-section dataset, and analyze the complex interrelationships between market integration and trust via an instrumental variables strategy (see below).

The most important variables are summarized in Table 5.1. From the original data set of 1800 observations we omitted those households which we do not observe in both waves, and we also omitted those with total expenditures in the 99th expenditures percentile because we suspect some of these are plagued by either measurement error or wrong data entry. As a result, the largest sample available for our analysis includes 1633 households—but we still have many missing observations for some of the variables of interest. The summary statistics of this data set are presented under Sample 1 in Table 5.1.

[48] Of the three study regions included in this Challenge Programme, detailed household expenditure data are available only for the Kano-Katsina-Maradi region, and hence we could not use data for the other two regions.

Table 5.1: Variable definitions and descriptive statistics

		Sample 1				Sample 2			
Variables	Definitions	count	mean	min	max	count	mean	min	max
A. Trust Variables									
Trust	equals 1 if someone generally trusts others, 0 otherwise	1415	0.60	0	1	1177	0.62	0	1
Trust in people from same village	equals 1 if someone rates his or her trust in people from same village above 3 in categorical question (1-no trust, 5-complete trust), 0 otherwise	1531	0.82	0	1	1159	0.83	0	1
Trust in complete strangers	equals 1 if someone rates his or her trust in complete strangers above 3 in categorical question (1-no trust, 5-complete trust)	1427	0.32	0	1	1081	0.34	0	1
B. Expenditure variables									
Total expenditure	Log (1+sum of food expenditure and non-food expenditure [1000 international dollars])	1521	2.27	0	5.38	1177	2.22	0.064	5.38
Food expenditure	Log (1+ annual food expenditure of household [1000 international dollars])	1521	0.826	0	4.20	1177	0.80	0	4.20
Non-food expenditure	Log (1+ total of annual cloth, education, repairs, health, expenditure of household, [1000 international dollar])	1549	2.10	0	5.25	1177	2.05	0	5.25
C. Control variables									
FCS	food consumption score, weekly.	1567	62.38	2.92	108.5	1177	62.9	2.92	108.5
Income	log (annual income of household, 2010, in current US dollars)	1091	8.07	-3.37	12.22	793	8.07	-3.28	12.11
Durable Goods	number of different types of durable assets owned by household	1567	4.14	0	10	1177	4.13	0	10
Male	equals 1 if household head is male, 0 otherwise	1631	0.96	0	1	1177	0.95	0	1
Household size	number of members of the household	1618	13.17	1	110	1177	12.74	1	102
Age	age of household head	1626	49.60	18	100	1177	49.5	20	100
Education	equals 1 if household head has graduated from primary school, 0 otherwise	1589	0.20	0	1	1177	0.19	0	1
Religious group	equals 1 if a member of household is a member of a religious group or cultural group, 0 otherwise	1487	0.43	0	1	1177	0.43	0	1
Extension policy	equals 1 if household leaves in a village where extension policies have been applied before 2008, 0 otherwise	1633	0.33	0	1	1177	0.32	0	1
Mobile network	equals 1 if there is mobile network coverage in the village household lives in, 0 otherwise	1633	0.92	0	1	1177	0.92	0	1
D. Instruments									
Markets within 50km radius	log(1+Number of output markets within 50km radius of the village in 2008)	1623	1.77	0	4.39	1177	1.71	0	4.39
Markets within village	log(1+ Number of output markets within the village in 2008)	1604	0.22	0	1.79	1162	0.20	0	1.79
E. Institutional Quality									
Others trust in local government	equals to 1 for a household if average trust in local government officials of other people living in the same village is higher than 3, 0 otherwise	1357	0.55	0	1	1112	0.59	0	1

Panel A of Table 5.1 contains 3 complementary trust measures, based on variations of the conventional survey questions as used in the World Value Survey. One question asked was the following: "Generally speaking would you say that most people can be trusted, yes or no?" This first question seeks to measure somebody's overall or general trust attitude, capturing a combination of "personalized and generalized trust." Next, respondents were asked to state, from a range from 1 (very poor) to 5 (very good), how they would describe their trust in people from the same village, and also their trust in complete strangers. Our second trust measure thus focuses on (within-village) personalized and repeated exchange and serves as our proxy of "personalized trust", and our third trust measure captures "generalized trust" as it is most closely related to the type of trust that fosters anonymous market exchange. Since the first trust variable was collected as a binary variable ("trust or no trust in most people"), we also converted the other two (categorical) trust variables (regarding other people in the same village, and regarding complete strangers) into binary ones. A trust score of 4 or 5 on the 5-point scale is transformed into a score of 1, and a categorical score of 1, 2 or 3 is coded as zero. In our sample trust in complete strangers is lower than trust in people from the same village whereas level of general trust is in between these two.[49]

Panel B in Table 5.1 contains our market integration proxies. Similar to Heinrich et al. (2004), we want to measure the importance of market exchange for households. Henrich et al. uses share of household's total calorie that is purchased from the market as a proxy for market integration Unfortunately we do not have information on the share of calorie purchased from the market; therefore we consider three variables, which are close proxies of Henrich et al.'s (2010) measure and summarize the monetary transactions of households with others: Total expenditures, food expenditures and non-food expenditures (including expenditures on repairs, education, health and clothing). To guarantee that these variables indeed capture market integration, and not wealth or income, we control for the latter two in our regressions. Also, purchased food may be a small portion of total food consumption, and may not reflect the true market integration of the families if subsistence

[49] We also estimate all the models by using the original categorical variables to test the robustness of our estimates and discuss them below while introducing our robustness checks.

production is common and households usually consume self-produced food. Therefore, we exploit another indicator of market integration, and that is the purchases of non-food commodities that cannot conceivably be produced within the household. We also control for household size, so our expenditure data do not pick up that some households are larger than others. Since our expenditure data are skewed, we take their natural logarithm in what follows.[50]

Hence, similar to Henrich et al., we measure integration in markets involving money[51] and increased expenditures should measure the importance of market transaction in the villagers' life as opposed to subsistence production. Expenditures may be a better measure than some other market integration indicators that have been used in the literature such as agricultural sales, access to roads, or labor market participation. Those indicators measure interaction of economic agents with only one market (e.g. labor market, crop market, input markets, and etc.), whereas expenditures are summary indicator for the transactions during purchase of goods and services in many different markets.[52]

These, and other, control variables are summarized in Panel C of Table 5.1. FCS measures total food consumption within a certain time period (a week), capturing both subsistence production and food purchased on the market. The "durable good" variable is intended to pick up ownership of assets, and hence is a proxy of wealth. The other variables are included in some of the analyses below to control for factors known to be correlated with trust, and should shrink the confidence intervals associated with our coefficients of interest. These controls include the age, gender and religious group

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[50] Because some households are subsistence farmers with zero expenditures, we construct the expenditure variables by taking the natural logarithm of 1 + "expenditures in 1000s of international dollars" rather than by taking the logarithm of "expenditures in 1000s of international dollars" directly.

[51] Integration to markets involving money vs. barter (gift) exchange markets may have different impacts on the evolution of personalized and generalized norms. Reciprocal and personalized exchanges are more likely in barter and gift exchange economies than market exchange (Kranton, 1994), and therefore integrating to them may develop personalized morals sustaining reciprocity in gift markets, and may hinder generalized norms (Platteu, 1994). On contrary, reciprocal and personalized relationships are not necessary in monetary markets; therefore positive impact of integration to markets involving money may not have a positive impact on personalized trust.

[52] To our knowledge there are only two additional measures for market integration that have been used in empirical studies: Access to weather roads (Jakiela, 2011) and sales to the market (Siziba & Bulte, 2012).

membership status of the household head, and whether or not a mobile phone network and/or an agricultural extension policy[53] are in place in the village.

Panel D of Table 5.1 summarizes the instruments we use to identify exogenous variation in potentially endogenous regressors of interest—market integration. The instruments are the number of markets within a 50 km radius, and the number of (local) markets in the village in which the household resides. We speculate the presence of (local) markets lowers transaction costs and encourages market exchange, but does not affect extant trust levels other than via market integration. Below we provide the results of specific tests to support these assumptions. As Table 5.1 documents, there are missing observations for quite a few variables of interest among the 1633 households in Sample 1. These variables include trust measures, expenditure proxies and control variables. To be able to compare our estimates for different trust measures, market integration proxies and regression models within the same sample, we report main estimation results using a subsample of 1177 households. The summary statistics of these households are presented under Sample 2 in Table 5.1. According to the relevant tests, robustness checks, and instrumental variable regression results (see robustness related discussion below)[54], our estimates do not change when using 1633 or 1177 households.

[53] Agricultural extension policies include introduction of improved variety crops, education for the application of chemical fertilizers and pesticide application and soil and water conservation techniques via extension agents who works for government officials or NGOs active in the region or in cooperation with them.

[54] We have tested whether there are systematic differences between complete and incomplete questionnaires in terms of trust measures. We regress a dummy variable (equal to 1 if at least one of the trust measures is missing for a household) on the total expenditure and control variables by using probit estimation technique and robust standard errors clustered at village level. We find that membership to religious group (-) and one of the province fixed effects enters significantly. Among the estimations religiosity is positively correlated only with general trust (See Table-2). We also tested whether that estimation result change according to religiosity of the households and find that there is no significant difference. For this reason we believe that attrition due to missing trust measures does not bias our results. Additionally, our main instrument is missing for only one village and if there is any selection bias due to attrition of households in OLS and Probit estimates, this will be corrected in 2SLS procedure assuming it is exogenous.

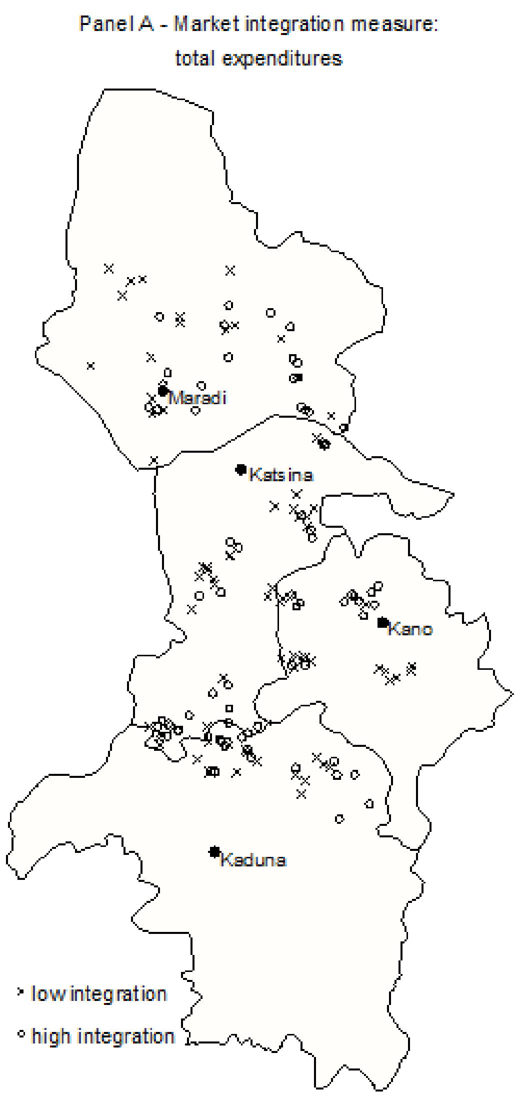

Figure 5.1: Spatial distribution of villages by provinces and market integration levels

Finally, Figure 5.1 shows the spatial distribution of the villages and the level of market.[55] To measure market integration, we use village level average of *total expenditures* and *number of markets within 50km radius around the villages* in Panels A and B respectively, and define the villages below (above) median regional integration level as low (high) market integration villages. Villages below (above) median regional integration level are defined as low (high) integration villages and marked by x (hollow circle), and the

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[55] We illustrate fewer villages in the Figure than we have in the original sample, as the coordinates for many villages are missing.

economic centre of each state is shown by squares. The Figure shows that high (low)-integrated villages are not spatially concentrated in certain regions; hence spatial correlation is not a major concern. Moreover market integration appears to be uncorrelated with distance to economic centres, as both high and low integrated villages are located close to the state economic centres. Yet, circumventing any concern, we will control for distance economic centres in the regression analysis discussed in the robustness checks.

5.3 Does market integration foster trust?

Does increased market integration affect the likelihood of trusting others? We estimate the following model:

(5.1) $Y_{\mathrm{iv}} = \gamma_0 + \gamma_1 E_{\mathrm{iv}} + X'_{\mathrm{iv}}\, \beta + \varepsilon_{\mathrm{iv}}$,

where i and v denote household i and village v, $\varepsilon_{\mathrm{iv}}$ denotes an error term, X_{iv} refers to a vector of household and village level controls, and E_{iv} measures the extent to which the household is integrated in markets. Y_{iv} measures trust (personalized or generalized trust), and since this variable is a dummy we commence by estimating (5.1) using a probit specification. In all models we cluster standard errors at the village level and also control for unobserved state level effects by including dummy variables for each state/region. The thesis that market integration fosters trust is supported if $\gamma_1 > 0$.

As stated above, we have three different trust measures (a general trust measure, a measure capturing personalized trust, and a measure reflecting trust in complete strangers), and we have three different indicators of market integration (total expenditures, and expenditures of food and on non-food items). This gives rise to 9 different Probit regression models. After having converted the coefficients into marginal effects, we present the results in Table 5.2.

Table 5.2 Market integration and trust-full specifications for Probit estimations

VARIABLES	General Trust	General Trust	General Trust	Trust in people from same village	Trust in people from same village	Trust in people from same village	Trust in complete strangers	Trust in complete strangers	Trust in complete strangers
Total Expenditure	-0.0652***			-0.0353***			-0.0567***		
	(0.0167)			(0.0122)			(0.0171)		
Food Expenditure		-0.0576***			-0.0267*			-0.0370*	
		(0.0203)			(0.0152)			(0.0195)	
Non-food expenditure			-0.0633***			-0.0342***			-0.0535***
			(0.0164)			(0.0121)			(0.0166)
FCS	0.00182**	0.00195**	0.00179**	0.00236***	0.00241***	0.00234***	0.00253***	0.00267***	0.00251***
	(0.0009)	(0.0009)	(0.0009)	(0.0005)	(0.0005)	(0.0005)	(0.0009)	(0.0009)	(0.0009)
Assets	0.0203**	0.0160*	0.0207**	0.00628	0.00384	0.00652	-0.000398	-0.00471	-0.000139
	(0.0085)	(0.0085)	(0.0085)	(0.0075)	(0.0074)	(0.0075)	(0.0085)	(0.0081)	(0.0085)
Gender	0.161**	0.145**	0.160**	0.0326	0.0235	0.0312	-0.0330	-0.0515	-0.0367
	(0.0642)	(0.0634)	(0.0638)	(0.0436)	(0.0439)	(0.0434)	(0.0720)	(0.0734)	(0.0720)
Age	0.000436	0.000185	0.000400	-0.000847	-0.000954	-0.000879	1.09e-05	-0.000280	-1.94e-05
	(0.0012)	(0.0012)	(0.0012)	(0.0008)	(0.0009)	(0.0008)	(0.0012)	(0.0012)	(0.0012)
Education	0.0230	0.0195	0.0213	-0.0355	-0.0365	-0.0371	0.0111	0.00487	0.0100
	(0.0372)	(0.0374)	(0.0370)	(0.0316)	(0.0325)	(0.0317)	(0.0430)	(0.0426)	(0.0432)
Household Size	0.00213	0.00238	0.00198	0.00130	0.00128	0.00122	0.00138	0.00165	0.00127
	(0.0017)	(0.0017)	(0.0017)	(0.0014)	(0.0014)	(0.0014)	(0.0017)	(0.0018)	(0.0017)
Religious group membership	0.0771**	0.0782**	0.0793**	0.00780	0.0101	0.00870	0.0255	0.0297	0.0279
	(0.0315)	(0.0313)	(0.0316)	(0.0248)	(0.0251)	(0.0247)	(0.0327)	(0.0327)	(0.0328)
Extension policy	-0.0768**	-0.0735**	-0.0786**	-0.0400	-0.0384	-0.0408	-0.00931	-0.00695	-0.0106
	(0.0364)	(0.0367)	(0.0364)	(0.0257)	(0.0259)	(0.0257)	(0.0349)	(0.0357)	(0.0349)
Mobile Network	0.0198	0.00141	0.0183	0.0294	0.0146	0.0293	-0.0667	-0.0880	-0.0691
	(0.0613)	(0.0632)	(0.0613)	(0.0441)	(0.0444)	(0.0440)	(0.0489)	(0.0539)	(0.0493)
Observations	1177	1177	1177	1159	1159	1159	1081	1081	1081
Method	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit

Notes: Robust standard errors clustered at village level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Coefficients reflect marginal effects at the variable's mean. Province fixed effects are added to the model but not reported in the table.

Before turning to the coefficients on the key variables of interest, our three different measures of market integration, note that all other covariates perform similarly across all nine specifications. Importantly, household size, total assets and food consumption score (FCS) are included to control for the amount of expenditures (on food and/or on non-food items) that are associated with the number of mouths to be fed, food intake, and wealth – leaving the expenditure variables to capture the impact of market integration on trust. FCS is positive and significant in all 9 regression models, while household size is never significantly different from zero. The performance of the assets variable is more unequal; it is significant (at the 5 or 10% level) in explaining general trust, but it is not significantly correlated to personalized trust or generalized trust. Most importantly, regarding the correlation between our measures of market integration and the three types of trust, the results are very robust – we invariably find that households that are better integrated in the local economy tend to place less trust in both people from the same village and in complete strangers. The same negative correlation results when using general trust as our dependent variable – we find $\gamma_1 < 0$ in all nine models.

The results in Table 5.2 are obtained using standard probit regression analysis, which pick up correlations, but not necessarily causal relations. There may be unobserved factors that are correlated with both market integration measures and trust, or - even though it is less likely[56] - a reverse causality problem may exist if low trust agents are more likely to actively participate in markets. To circumvent the quite stringent assumptions underlying IVprobit (especially regarding joint normality of the error terms[57]; Wooldridge 2002), we proceed as follows. We first re-estimate the nine models presented in Table 5.2 using OLS, and check whether the coefficients obtained are qualitatively similar to the ones obtained using Probit. Next, we run 2SLS models for all nine specifications to allow for causal interpretations of the coefficients obtained. The 2SLS model we employ is specified as follows. We "predict" E_{iv} using the following equation:

[56] We may expect that people who trust more are more likely to move towards markets and existence of this selection effect make our results stronger, as the selection will bias our estimates positively and make them converge to zero. So the estimates are big enough to be statistically significant and negative even if there is even such a selection bias.

[57] In IVprobit, our first stage error term might violate the normality assumption because both the dependent and instrumental variables are censored at zero as we use log(1+x) of both (see above).

(5.2) $E_{iv} = \alpha_0 + M_v' \alpha_1 + X'_{iv} \alpha_2 + \mu_{iv}$,

where μ_{iv} denotes the error term and M is a vector of excluded instruments. Our main instrument is the number of markets which are *not* located in the village but which are within a 50 km radius of the village in 2008.[58] We expect a positive correlation between our market integration and instrument as more markets around the village mean more opportunities for trade and exchange for households. Our identification strategy rests on the usual assumptions that (1) the instrument is strongly correlated with expenditure variables, and (2) the number of markets around the village is not correlated with unobserved village level factors that may be correlated with market integration measures. To show whether the first assumption holds, we test the level of significance of our instruments in the first stage estimations, and report the F-statistics (see below). To satisfy the second assumption, we utilize information from detailed survey questions, and control for the omitted factors that may be correlated with both number of markets and trust levels. Hence, we add various village level control variables to our 2SLS model and test the consistency of our estimates to inclusion of those in robustness checks.

We also use the number of markets in the village as an additional instrument in robustness checks. Because the number of markets within the village is not a strong predictor of one of our measures of market integration, food expenditures, we consider our estimations based on a single instrument (number of markets within 50km) as our main or preferred set of estimates. The outcomes of models with both instruments serve as a robustness check, and we are mainly interested in checking the consistency of our results.

Using (5.2) we calculate predicted values of E_{iv}, which we subsequently use in (5.1). We thus re-ran the same 9 specifications that were used in the Probit regressions (as already presented in Table 5.2) and also use OLS and 2SLS. We present the key results of all 27 regressions in Table 5.3. To economize on space we do not report the full outcomes of all these regression models – instead, Table 5.3 only presents the 27 estimates of γ_1, the coefficient on the relevant measure of market integration. The full regression results of the

[58] The instrument is constructed by using survey questions asking how many markets are there within 50km radius and in the village; no usable information is available about the distance to the closest market measures – but see footnote 15.

2SLS models are presented in Table A.5.1 in the Appendix, while the exact regression results of the OLS models are available upon request.[59] Our main result is that, in contrast to the theoretical prediction that $\gamma_1>0$ and despite the fact that we are controlling for key factors like income, wealth and household size, we find that all 27 estimates are *negative* and significant. Estimation results imply 50 percent increase in total expenditures – which is a plausible scenario in our study context where sample average and standard deviation for total expenditures equals to 16 and 30 U.S dollars respectively - decreases the likelihood of general, personal and generalized trust by 41, 12 and 20 percentage points respectively.

While the OLS and Probit coefficients are of roughly equal size (recall that we converted the Probit coefficients into marginal effects), the 2SLS coefficients are considerably larger, but the estimates are less precise as the standard errors are higher. This may reflect that measurement errors in market integration indicators, which lead to a downward bias in OLS and Probit estimates, are large, or that the Probit and OLS correlations pick up a significant opposite effect (i.e., trust promoting trade).[60] The estimation results of the first stage of our 2SLS models, including various test statistics, support our instrumentation strategy and suggest there is no weak instrument problem. Specifically, the F-values of the excluded instrument are much higher than 10 in all regressions (see Table A.5.1 for details).[61]

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[59] The coefficients of the OLS regressions on all the covariates other than γ_1, are very similar to the coefficients obtained in the second stage of the 2SLS models. Including these here would thus not provide any useful new insights.

[60] Unfortunately, the data do not permit us to usefully explore this reverse relationship. As stated in section 2, the expenditure data were collected in the first wave of data collection in 2008, while the trust data were elicited in the second wave, in 2010. While the timing of data collection strengthens our beliefs that the relationship uncovered in the 2SLS regressions are indeed causal, a similar analysis of the reverse relationship would only be reliable if trust would be time-invariant.

[61] Weak instruments is less of a concern in our just identified models, in which we use one excluded instrument. (See Angrist and Pischke,2009, p.209).

Table 5.3: The coefficients of Market Integration in 27 regression models explaining Trust

	General Trust			Trust in people from same village			Trust in complete strangers		
Market integration indicators	Probit	OLS	2SLS	Probit	OLS	2SLS	Probit	OLS	2SLS
Total Expenditure	-0.0652***	-0.0656***	-0.408***	-0.0353***	-0.0331**	-0.122*	-0.0567***	-0.0558***	-0.206***
	(0.0167)	(0.0172)	(0.122)	(0.0122)	(0.0132)	(0.0656)	(0.0161)	(0.0162)	(0.0776)
	[1177]	[1177]	[1177]	[1159]	[1159]	[1159]	[1081]	[1081]	[1081]
Food Expenditure	-0.0576***	-0.0570***	-0.581***	-0.0267*	-0.0261*	-0.172*	-0.0370*	-0.0354*	-0.287**
	(0.0203)	(0.0209)	(0.164)	(0.0152)	(0.0144)	(0.0975)	(0.0195)	(0.0184)	(0.115)
	[1177]	[1177]	[1177]	[1159]	[1159]	[1159]	[1081]	[1081]	[1081]
Non-food Expenditure	-0.0633***	-0.0636***	-0.432***	-0.0342***	-0.0317**	-0.130*	-0.0535***	-0.0524***	-0.221***
	(0.0164)	(0.0167)	(0.133)	(0.0121)	(0.0130)	(0.0699)	(0.0166)	(0.0158)	(0.0834)
	[1177]	[1177]	[1177]	[1159]	[1159]	[1159]	[1081]	[1081]	[1081]

Robust standard errors clustered at village level are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. For probit estimations, estimates of marginal effects at mean levels are shown. We control for household heads' education, age and gender; food consumption score of the household; membership to religious or cultural group; household size; number of durable assets in the household; whether agricultural extension policies have been applied in the village; existence of mobile network in the village; province fixed effects in the estimations. In IV regressions number of markets within 50km radius of the village household resides in is used as instrument.

When comparing the results for trust in people from the same village and to that in strangers, we observe that the eroding effect of market integration on trust is more pronounced for strangers than for fellow villagers. Both the correlations and the 2SLS causal estimates are almost twice as large for the generalized trust model as for the personalized trust model. While this is intuitive, as trade may intensify interaction with strangers and enlarge the probability of being cheated or disappointed by the behavior of trading partners, it is surprising to note that market integration also reduces personalized trust. Perhaps this reflects the gradual substitution of informal institutions and sharing arrangements for formal, market-mediated ones (cf. Ahlerup et al. 2009 for a theoretical analysis), setting in motion a process of erosion of village social capital.

We thus find that market integration (proxied by expenditures, controlling for income and food consumption) is associated with *lower* levels of general trust, personalized trust, and generalized trust. The negative coefficients in Table 5.3 are consistent with results by Siziba and Bulte (2012),[62] but opposite to those found by Henrich et al. (2010). The latter may be caused by the fact that Henrich et al. derive their trust variable from (incentive-compatible) experiments, rather than survey questions. However, while this methodological difference will undoubtedly affect point estimates (estimated "levels of trust") it is not obvious why it would reverse the comparative statics with respect to market integration. Next, while it may be easy to reconcile our 2SLS results with their OLS estimates – their correlations may pick up other dimensions of the complex interrelationship between trade and trust – it is puzzling that market integration enters negatively in our Probit and OLS models. Perhaps the sign reversal is due to differences in the way we operationalize market integration. Henrich et al. (2010) base their study on the percentage of calories consumed that is purchased on the market. Arguably our measure of food expenditures is comparable to this variable. However, controlling for the overall level of food consumption (the variable Food Consumption Score, based on the nutritional value of various food items consumed over a period of time – regardless of whether they are

[62] Siziba and Bulte (2012) use an RCT design to document a negative relation between market integration and stated trust among a sample of farmers in Mozambique. In a related vein (albeit not focusing on trust directly), Jakiela (2011) uses effort games in Kenya, and finds that proximity to markets decreases the level of offers in dictator games.

home-produced or purchased), the food expenditures variable also consistently enters with a negative sign. The same is true for non-food expenditures, so we do not believe our results are driven by specific features of food as a consumption item. Might the sampling difference in terms of market integration levels between our study and Henrich et al. explain the sign reversal? Henrich et al.'s study sample various communities from across the globe; it includes the communities that are fully integrated to the markets (such as the communities from U.S purchasing 100 percent of their diet at the markets) and also communities that are not integrated in the markets. We analyze households with moderate level of market integration; hence they fall within the spectrum covered by Henrich et al.

We followed several routes to probe the robustness of these findings. For example, we have estimated "parsimonious models" without controls, and also gradually added different combinations of control variables (gradually reducing sample size). Our main results, in particular those for general and generalized trust, go through for such more parsimonious specifications and larger sample sizes.[63] We also estimated all the models presented by treating generalized and personalized trust as categorical variables rather than binary ones (see Tables A.5.2 and A.5.3 in the Appendix for detailed estimation results). This generally does not affect the qualitative nature of our results for our generalized trust measure.[64] Similarly, we find that our results are robust to including alternative specifications of income. While monetary income measures are available for only a rather small sub-sample of our respondents, all results go through when focusing on this subsample and controlling for income.

[63] As an extra robustness test we also estimated a general model and replaced all missing values of the explanatory variables by zeros, combined with inserting dummies for these missing observations. This does not affect our results.

[64] When trust in complete strangers is our dependent variable, we find statistically significant and negative estimates for total expenditure and non-food expenditure variables in Ordered Probit and OLS estimations. When measuring market integration with food expenditures, the associated coefficient is again negative, but fails to be statistically significant at the 10% or better. We reach negative and statistically significant estimates for all expenditure variables in 2SLS where number of markets within 50km around the village used as the instrument and trust in complete strangers is the dependent variable. Moreover, these estimation results are robust when we estimate gradually adding control variables, control for income, and use number of markets in the village as an additional instrument in 2SLS estimations. However, for personalized trust variable our results are not robust with former estimates; the coefficient estimates for expenditure variables are negative but not negatively significant - except in Ordered Probit estimations where total nonfood expenditure is our main variable of interest.

As a further robustness check, we also included additional village level controls in our 2SLS models (a village poverty measure, population size, soil fertility[65], distance to closest economic centre[66] and dummy variables for village infrastructure[67]) to control for village characteristics such as urbanization level which may be correlated with trust and the location of the markets and trust. Again, our estimates are robust.[68] We have also re-estimated the various 2SLS models with both excluded instruments (rather than one), and the p-values of Hansen's J test consistently exceed 0.10 so we cannot reject the exogeneity of our instruments[69]. Additionally, we have estimated all models including both excluded instruments by using the LIML estimation technique (producing consistent outcomes when instruments are "weak"), and estimates are still robust with former estimates. We also estimate IV Probit models to test the robustness of the 2SLS outcomes. We found, again, that all results summarized in Tables 5.2 and 5.3 are robust to such extensions. Details of all results are available upon request.

We thus find no support for a "virtuous cycle" between market integration and trust, as market integration decreases trust for the average household. This analysis is based on the assumption that the relationship between market integration and trust is orthogonal to local institutional quality – which may not be the case in practice. To explore the role of instrumental quality as a mediating factor, we hypothesize that increased market integration

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[65] Our village level soil fertility measure is the categorical answers (1=the soil is poor to very poor…., 2=various crops can be grown in this soil …, 3=the soils are rich in nutrients and humus content…) to the question "How would you assess soil fertility?" by extension workers.

[66] To construct the distance to closest economic centre measure, we used geographic coordinates of the villages for which data are available, and the coordinates of the economic centres of Kaduna, Katsina, Kano and Maradi provinces (the provinces closest to the villages used in the study). We calculated the geographic distances of each village to those provinces' centres, and then we used the minimum distance among the four for each village.

[67] The set of dummy variables for infrastructure (equal to 1 if a specific kind of infrastructure is present in the village) include schools, health centers (hospitals, clinics), places of worship (churches, mosques), community structures (meeting halls, centers), irrigation infrastructures (boreholes, wells), veterinary extension services (cattle dips, veterinary centres), village wood lots, land line telephones, mobile phone network radio reception, newspapers, all weather roads; water bodies, livestock watering points, public transport stops, rural micro-finance banks, government extension offices for agriculture and livestock, agriculture research site.

[68] The coefficient on market integration in the personalized trust model is negative but is not statistically significant. When we control for the coefficients on distance to closest economic centres in trust in complete strangers models, the coefficients on market integration and distance to closest economic centres are not statistically significant.

[69] This is a valid test for the exogeneity only if one of the instruments, number of markets within or around 50km radius, is exogenous.

reduces trust because not all market transactions are completed truthfully and faithfully. We tentatively test this by analysing whether high-quality local institutions attenuate the negative causal effect of market integration on trust. If households can resort to arbitration by formal institutions in case of trade conflicts, they are less likely to be exploited in the trade relationship. If so, faith in trading partners may not erode as fast as in regions where households cannot resort to formal institutions.

Unfortunately, the survey does not contain any truly exogenous institutional quality measure, but it does contain a question on villagers' trust in local government institutions. Perhaps the average level of trust of co-villagers in the local government is a good proxy of institutional quality while at the same time being exogenous to the household level trust. We construct a dummy variable for institutional quality that is equal to 1 if the average trust in the local government of all other households in a village exceeds 3.[70] The 2SLS results[71], for each of the two subgroups, are presented in Table 5.4, where we again instrument for market integration by the number of markets within a 50km distance.

The results are robust and interesting. While the coefficient on the predicted level of market integration continues to be negative and significant in villages with low (perceived) institutional quality, the estimates are still negative but either imprecisely estimated (general trust) or lower for personalized and generalized trust, and as a result they are not statistically significant in villages with high institutional quality. We may thus find support for a trap mediated by formal institutions: Villages are locked into a low trust, low market integration situation, unless the quality of local institutions is sufficiently good; high trust households starting to trade with strangers may lose their trust if the institutional quality is low, and therefore eventually do not participate in the market.

[70] For the definition and descriptive statistics of the institutional quality variable, see Panel E in Table 1. We exclude the villages where trust in local government officials reported by less than 4 households, since such small numbers of villagers likely produces a very noisy measure of the quality of institutions. This explains why these models are based on a slightly smaller sample.
[71] Estimates from OLS models are similar to 2SLS estimates.

Table 5.4: Market integration and Trust: Heterogeneity with respect to institutional trust in local government

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var:	General Trust		Trust in people from same village		Trust in complete strangers	
	Others' trust in loc. gov.=0	Others' trust in loc. gov.=1	Others' trust in loc. gov.=0	Others' trust in cent. loc.=1	Others' trust in loc. gov.=0	Others' trust in loc. gov.=1
Total Expenditure	-0.430***	-0.490	-0.193***	-0.0477	-0.227***	-0.104
	(0.1395)	(0.3697)	(0.0671)	(0.1636)	(0.0695)	(0.2971)
FCS	0.00206	0.000539	0.00154	0.00219***	0.00195*	0.00167
	(0.0016)	(0.0013)	(0.0010)	(0.0007)	(0.0011)	(0.0014)
Assets	0.0425*	0.0443**	0.0335**	-0.00183	0.0325**	-0.00804
	(0.0228)	(0.0174)	(0.0135)	(0.0097)	(0.0133)	(0.0164)
Gender	0.349***	0.345**	0.142	0.0428	0.165**	-0.102
	(0.1164)	(0.1669)	(0.1274)	(0.1117)	(0.0663)	(0.1369)
Age	0.00429	0.00240	0.000923	-0.00192	0.00106	0.000321
	(0.0027)	(0.0030)	(0.0018)	(0.0016)	(0.0017)	(0.0025)
Education	0.0515	0.0889	-0.0410	-0.0146	-0.0242	0.0837
	(0.0884)	(0.0733)	(0.0520)	(0.0380)	(0.0512)	(0.0760)
Household size	0.000783	0.00171	-0.000559	0.00287**	-0.00208	0.00493*
	(0.0031)	(0.0025)	(0.0026)	(0.0012)	(0.0020)	(0.0026)
Religious group mem.	-0.0350	0.0594	-0.0315	0.0150	0.0325	-0.0220
	(0.0580)	(0.0608)	(0.0414)	(0.0334)	(0.0495)	(0.0497)
Extension policy	-0.0171	-0.138**	-0.0334	-0.0532*	-0.000734	-0.0225
	(0.0764)	(0.0585)	(0.0467)	(0.0319)	(0.0413)	(0.0513)
Mobile network	0.122	0.294	0.167*	-0.0124	0.0393	-0.0540
	(0.0982)	(0.1812)	(0.0896)	(0.1061)	(0.0600)	(0.1544)
Constant	0.287*	0.481**	0.583***	0.725***	0.0817	0.513**
	(0.1542)	(0.2404)	(0.1721)	(0.1268)	(0.1083)	(0.2074)
Observations	460	652	457	652	442	612
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Root mean sq. error	0.561	0.568	0.392	0.325	0.417	0.481
F-stat (Instrument)	22.17	4.763	22.15	4.763	22.39	3.896

Notes: Robust standard errors clustered at village level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Number of markets within 50km radius households resides in used as instrument for total expenditure. Province fixed effects are added to the model but not reported in the table.

5.4 Discussion and conclusions

We use data on 1633 households in Niger and Northern Nigeria to test whether market integration fosters trust. If trade and trust are complements in development, policy interventions that increase either trust or market integration would put autarchic societies on a "virtuous" trajectory of increasing prosperity and trust. We seek to extend Henrich et al.'s (2010) ground-breaking work by focusing on within-country variation in market integration and trust, and by identifying exogenous variation in market integration (via an instrumental variables approach). Using three measures of market integration (expenditures on food, expenditures on non-food items and expenditures on both) and controlling for wealth and food intake, we find that increased market integration *reduces* trust.

Closer inspection reveals this effect is entirely driven by villages with low-quality local institutions. In other words, the trust-eroding effect of market integration is mediated by the quality of local institutions, and virtuous cycles between trade and trust may exist—but only if the quality of institutions is sufficient high. We believe this has important implications for policy makers. Specifically, in a context of "low institutional quality" it will be difficult to kick-start processes of increasing trade and trust. Improving the quality of local governance and institutions, or building local confidence therein, seems a pre-condition for virtuous cycles to emerge.

Opportunities for improvement remain. First, one may doubt whether the density markets is an exogenous measure. Our instrument satisfies the exclusion and relevance tests, and the results are robust. However, we are constrained by the dataset, and there may be still unobserved factors that we do not control for and correlated with both market integration and trust measures. Hence, we recognize that there is need for future research utilizing quasi-experimental variation in market integration. Second, our measure of institutional quality is not perfect, and we believe that studying the channels through which market integration affects trust is an important issue for future work.

5.A Appendix: Additional tables

Table A.5.1: The second stage regression results

VARIABLES	(1) General trust	(2) General trust	(3) General trust	(4) Trust in people from the same village	(5) Trust in people from the same village	(6) Trust in people from the same village	(7) Trust in complete strangers	(8) Trust in complete strangers	(9) Trust in complete strangers
Total Expenditure	-0.408***			-0.122*			-0.206***		
	(0.1220)			(0.0656)			(0.0776)		
Food Expenditure		-0.581***			-0.172*			-0.287**	
		(0.1633)			(0.0975)			(0.1152)	
Nonfood Expenditure			-0.432***			-0.130*			-0.221***
			(0.1333)			(0.0699)			(0.0834)
FCS	0.00131	0.00223*	0.00101	0.00238***	0.00267***	0.00228***	0.00230**	0.00279***	0.00214**
	(0.0010)	(0.0012)	(0.0010)	(0.0006)	(0.0006)	(0.0006)	(0.0010)	(0.0010)	(0.0010)
Assets	0.0414***	0.0120	0.0471***	0.0107	0.00157	0.0125	0.00908	-0.00650	0.0121
	(0.0128)	(0.0115)	(0.0142)	(0.0082)	(0.0076)	(0.0088)	(0.0104)	(0.0087)	(0.0113)
Gender	0.304***	0.245***	0.307***	0.0953	0.0743	0.0958	0.0372	0.00153	0.0358
	(0.0920)	(0.0863)	(0.0924)	(0.0733)	(0.0709)	(0.0728)	(0.0736)	(0.0730)	(0.0731)
Age	0.00268*	0.00184	0.00264	-0.000456	-0.000719	-0.000455	0.000957	0.000471	0.000957
	(0.0016)	(0.0016)	(0.0016)	(0.0011)	(0.0010)	(0.0010)	(0.0013)	(0.0013)	(0.0013)
Education	0.0711	0.0740	0.0644	-0.0170	-0.0158	-0.0190	0.0321	0.0316	0.0300
	(0.0515)	(0.0582)	(0.0514)	(0.0301)	(0.0320)	(0.0302)	(0.0476)	(0.0489)	(0.0487)
Household size	0.00176	0.00475**	0.000776	0.000985	0.00183	0.000698	0.00153	0.00315	0.00102
	(0.0019)	(0.0023)	(0.0020)	(0.0012)	(0.0013)	(0.0012)	(0.0016)	(0.0020)	(0.0016)
Religious group mem.	0.0225	-0.00181	0.0320	-0.00697	-0.0133	-0.00436	0.00303	-0.0102	0.00760
	(0.0388)	(0.0436)	(0.0389)	(0.0262)	(0.0281)	(0.0258)	(0.0358)	(0.0400)	(0.0357)
Extension policy	-0.0703	-0.0318	-0.0817*	-0.0440	-0.0322	-0.0471*	-0.00734	0.0116	-0.0129
	(0.0434)	(0.0471)	(0.0446)	(0.0281)	(0.0285)	(0.0283)	(0.0336)	(0.0372)	(0.0334)
Mobile network	0.166**	0.0821	0.172**	0.0768	0.0520	0.0787	-0.00516	-0.0539	0.000460
	(0.0827)	(0.0771)	(0.0849)	(0.0577)	(0.0493)	(0.0585)	(0.0624)	(0.0626)	(0.0634)
Constant	0.447***	0.262**	0.423***	0.616***	0.562***	0.610***	0.359***	0.272**	0.351***
	(0.1375)	(0.1321)	(0.1362)	(0.0974)	(0.1001)	(0.0970)	(0.1222)	(0.1210)	(0.1208)
Observations	1,177	1,177	1,177	1,159	1,159	1,159	1,081	1,081	1,081
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
F stat. (Instrument)	21.45	19.27	20.25	20.44	19.87	19.05	22.34	22.01	20.18
RMSE	0.550	0.599	0.566	0.364	0.371	0.366	0.466	0.485	0.471

Notes: Robust standard errors clustered at village level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Province fixed effects are added to the model but not reported in the table.

Table A.5.1 (continued): First stage regression results

VARIABLES	(1) Total Exp.	(2) Food Exp.	(3) Non-food Exp.	(4) Total Exp.	(5) Food Exp.	(6) Non-food Exp.	(7) Total Exp.	(8) Food Exp	(9) Non -food Exp.
Markets within 50km radius	0.292***	0.205***	0.275***	0.291***	0.206***	0.273***	0.307***	0.221***	0.287***
	(0.0630)	(0.0466)	(0.0612)	(0.0644)	(0.0463)	(0.0625)	(0.0650)	(0.0470)	(0.0639)
FCS	-0.000337	0.00134	-0.00102	-0.000562	0.00129	-0.00128	-0.000755	0.00114	-0.00143
	(0.0012)	(0.0010)	(0.0013)	(0.0012)	(0.0010)	(0.0013)	(0.0013)	(0.0011)	(0.0014)
Assets	0.0568***	-0.0108	0.0669***	0.0592***	-0.0109	0.0694***	0.0618***	-0.00991	0.0715***
	(0.0178)	(0.0156)	(0.0175)	(0.0179)	(0.0156)	(0.0176)	(0.0184)	(0.0160)	(0.0182)
Gender	0.323***	0.124	0.313***	0.388***	0.153*	0.368***	0.398***	0.161*	0.365***
	(0.1057)	(0.0811)	(0.1007)	(0.1025)	(0.0789)	(0.0982)	(0.1224)	(0.0913)	(0.1159)
Age	0.00552**	0.00244	0.00513**	0.00561**	0.00245	0.00527**	0.00548**	0.00224	0.00511**
	(0.0022)	(0.0018)	(0.0023)	(0.0022)	(0.0018)	(0.0023)	(0.0023)	(0.0019)	(0.0024)
Education	0.145*	0.107	0.122	0.143	0.108	0.119	0.154*	0.109	0.134
	(0.0851)	(0.0794)	(0.0840)	(0.0870)	(0.0814)	(0.0861)	(0.0882)	(0.0828)	(0.0872)
Household Size	0.000193	0.00527*	-0.00210	0.000543	0.00529*	-0.00169	-0.000243	0.00547*	-0.00255
	(0.0039)	(0.0029)	(0.0039)	(0.0039)	(0.0029)	(0.0040)	(0.0039)	(0.0030)	(0.0040)
Religious group membership	-0.103**	-0.114***	-0.0750	-0.110**	-0.115***	-0.0832	-0.101*	-0.118**	-0.0737
	(0.0517)	(0.0434)	(0.0531)	(0.0516)	(0.0439)	(0.0531)	(0.0542)	(0.0463)	(0.0557)
Extension policy in	0.0232	0.0824	-0.00447	0.0116	0.0765	-0.0133	0.0154	0.0769	-0.0106
place	(0.0713)	(0.0531)	(0.0718)	(0.0717)	(0.0536)	(0.0718)	(0.0731)	(0.0550)	(0.0734)
Mobile Network	0.332**	0.0890	0.328**	0.334**	0.0929	0.328**	0.381**	0.103	0.381**
	(0.1433)	(0.0911)	(0.1416)	(0.1456)	(0.0917)	(0.1441)	(0.1532)	(0.0944)	(0.1516)
Constant	-0.0544	-0.358**	-0.108	-0.112	-0.391**	-0.151	-0.177	-0.428**	-0.201
	(0.2233)	(0.1620)	(0.2248)	(0.2238)	(0.1622)	(0.2246)	(0.2393)	(0.1715)	(0.2424)
Observations	1,177	1,177	1,177	1,159	1,159	1,159	1,081	1,081	1,081
R-squared	0.360	0.202	0.334	0.363	0.204	0.335	0.345	0.200	0.315
2nd stage dep. var.	General Trust	General Trust	General Trust	Trust in people from same village	Trust in people from same village	Trust in people from same village	Trust in complete strangers	Trust in people from outside village	Trust in complete strangers
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Note: Robust standard errors clustered at village level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Province fixed effects are added to the model but not reported in the table.

Table A.5.2 Market integration and trust in people from same village (categorical variables 1-5)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Total Expenditure	-0.08**			-0.04			-0.11		
	(0.04)			(0.03)			(0.16)		
Food Expenditure		-0.05			-0.03			-0.15	
		(0.05)			(0.03)			(0.22)	
Non-food expenditure			-0.08**			-0.04			-0.12
			(0.04)			(0.03)			(0.17)
FCS	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Assets	0.03	0.03	0.03	0.02	0.01	0.02	0.02	0.01	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Gender	0.07	0.05	0.07	0.02	0.01	0.02	0.05	0.03	0.05
	(0.14)	(0.14)	(0.14)	(0.15)	(0.15)	(0.15)	(0.16)	(0.15)	(0.16)
Age	0.00	-0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Education	-0.10	-0.11	-0.10	-0.06	-0.06	-0.06	-0.05	-0.05	-0.05
	(0.09)	(0.09)	(0.09)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Household Size	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Religious group membership	-0.01	-0.00	-0.01	0.00	0.00	0.00	-0.01	-0.01	-0.01
	(0.08)	(0.08)	(0.08)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)
Extension policy	-0.04	-0.04	-0.04	-0.07	-0.07	-0.07	-0.07	-0.06	-0.07
	(0.09)	(0.09)	(0.09)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)
Mobile Network	0.20	0.17	0.20	0.16	0.14	0.16	0.19	0.16	0.19
	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.13)	(0.16)	(0.14)	(0.16)
Constant				3.24***	3.22***	3.24***	3.26***	3.21***	3.26***
				(0.23)	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)
Observations	1159	1159	1159	1159	1159	1159	1159	1159	1159
Method	Ordered Probit	Ordered Probit	Ordered Probit	OLS	OLS	OLS	2SLS	2SLS	2SLS

Notes: Robust standard errors clustered at village level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Coefficients reflect marginal effects at the variable's mean. Province fixed effects are added to the model but not reported in the table.

Table A.5.3 Market integration and trust in complete strangers (categorical variables 1-5)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Total Expenditure	-0.09**			-0.09**			-0.59***		
	(0.04)			(0.04)			(0.21)		
Food Expenditure		-0.05			-0.05			-0.82***	
		(0.05)			(0.04)			(0.31)	
Non-food expenditure			-0.09**			-0.08**			-0.63***
			(0.04)			(0.04)			(0.22)
FCS	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01**	0.01***	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Assets	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.03	-0.02	0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
Gender	0.05	0.02	0.05	0.09	0.06	0.09	0.32	0.22	0.32
	(0.20)	(0.20)	(0.20)	(0.19)	(0.19)	(0.19)	(0.21)	(0.20)	(0.21)
Age	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Education	-0.07	-0.08	-0.07	-0.08	-0.09	-0.08	-0.00	-0.01	-0.01
	(0.10)	(0.10)	(0.10)	(0.08)	(0.08)	(0.09)	(0.10)	(0.11)	(0.10)
Household Size	0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Religious group membership	-0.01	0.00	-0.00	-0.01	-0.00	-0.00	-0.09	-0.13	-0.08
	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.10)	(0.09)
Extension policy	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.07	0.00
	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.08)
Mobile Network	-0.25*	-0.29**	-0.25*	-0.24*	-0.27**	-0.24**	0.01	-0.13	0.03
	(0.13)	(0.14)	(0.13)	(0.12)	(0.13)	(0.12)	(0.15)	(0.14)	(0.15)
Constant				2.52***	2.49***	2.52***	2.66***	2.42***	2.64***
				(0.29)	(0.29)	(0.29)	(0.30)	(0.31)	(0.30)
Observations	1159	1159	1159	1,081	1,081	1,081	1,081	1,081	1,081
Method	Ordered Probit	Ordered Probit	Ordered Probit	OLS	OLS	OLS	2SLS	2SLS	2SLS

Notes: Robust standard errors clustered at village level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Province fixed effects are added to the model but not reported in the table.

Chapter 6

Entrepreneurial saving practices and reinvestment: Theory and evidence from Tanzanian MSEs[§]

6.1 Introduction

In developing countries, intermediation costs and enforcement frictions constrain access to external finance by micro and small enterprises (MSEs) - leaving entrepreneurs' earning retention as a key element for small business growth. But, what drives entrepreneurial decisions to reinvest in their own businesses? Given the limited access to formal financial services, many entrepreneurs use informal mechanisms of saving and liquidity management to facilitate their earnings retention. In this paper, we utilize a novel dataset from Tanzania to explore whether entrepreneurial saving practices can explain variation in entrepreneurs' reinvestment decisions. Specifically, we gauge whether the decision to save with formal financial institutions, individually (under the mattress), within the household or via other informal arrangements, such as rotating savings and credit associations (ROSCAs), affect the decision to reinvest entrepreneurial earnings. We motivate our empirical work with a simple theoretical model that shows that an entrepreneur's reinvestment decision depends on the entrepreneur's saving practice, in addition to productivity and borrowing capacity of her entrepreneurial firm.

In the absence of easy access to external finance, saving for business purposes should be positively correlated with entrepreneurial investment. However, the saving mechanism itself might be a critical element in determining the ability to reinvest. On the one hand, for formal savers the opportunity cost of consuming business profits instead of

[§] This Chapter is based on following research paper: Beck, T., Pamuk, H., & Uras, B. R. (2014). *Entrepreneurial Saving Practices and Reinvestment: Theory and Evidence from Tanzanian* MSEs (Working Paper No. 2014-15). Centre for the Study of African Economies, University of Oxford.

reinvesting them is not only the loss of financial reserves but also the foregone interest income. On the other hand, for instance, the "informal savers" might be less likely to reinvest because of redistributive pressure on "with household members" from kin and family members. If the remaining household members are aware of the existence of entrepreneurial savings, it can be hard to prevent the funds from being exploited for the general consumption needs of the household. In addition to these two extreme cases, we could also think of the "individual savers" and the "informal finance network savers" as other saving practice types. Comparing "individual savers" with "informal network savers", we note that although the interest income from informal finance networks should have an impact on the opportunity cost of consumption and foster investment, the inflexibility to withdraw savings at informal financial institutions might offset this income effect and reduce the earnings retention.[72]

In order to inform our empirical hypotheses, we first present a simple theoretical model to explain the relationship between entrepreneurial investment decisions and saving practices. We show that entrepreneurs are more likely to invest in their businesses if they save in a fashion which allows them easy access to their funds, such as formal savings accounts or personal saving mechanisms.

To test the empirical relationship between savings patterns and entrepreneurial reinvestment decisions, we use an MSE survey held among over 6,000 Tanzanian entrepreneurs undertaken in 2010. The sample of entrepreneurs surveyed covers a large variety of enterprises in different locations, of different gender, educational profile and sectors. We document that entrepreneurs' saving *practices* do indeed co-vary with the likelihood of earnings retention at MSEs. The survey design allows us to differentiate between different savings vehicles, including within household saving, saving under the pillow, informal savings clubs, and formal deposit accounts. Our results reveal that the probability of reinvestment is significantly higher for savers and that when compared

[72] The rate of return to savings in social saving clubs is typically lower compared to formal financial institutions. For related discussion see Vonderlack and Schreiner (2002). Entrepreneurs saving via informal channels are more likely to have limited access to their savings. For instance, members of ROSCAs cannot access their savings until their turn comes (see Besley et al. (1993) for a theoretical discussion of ROSCAs), unless there is a relevant secondary market (Calorimis & Rajamaran, 1998). Similarly, moneylenders may postpone repaying the savings or it might be hard to reach them.

against formal deposit account holders, entrepreneurs who give their savings to other household members to keep them safe are significantly less likely to reinvest. Specifically, we find that when we compare the practice of keeping savings *within the household* against the practice of *having a deposit account at a formal financial institution*, the latter is more likely to be associated with reinvestment than the former.

We conduct a series of checks to ensure the robustness of our results to the inclusion of additional control variables and alternative model specifications. Furthermore, to address the potential reverse causation of high reinvestment on saving practices we utilize the distance to the nearest bank and entrepreneur's age as instruments in recursive bivariate probit regressions. Those variables can explain whether the savings will be kept in a bank account or shared with the rest of the household, but they are not directly associated with reinvestment decisions. The coefficient estimates in the instrumental variable regressions remain stable and significant across all specifications. Finally, we explore the differential effects of saving patterns on reinvestment decision across groups with different intra-household bargaining power. We find that the negative relationship between saving within the household and reinvestment decisions is stronger for entrepreneurs with lower intra-household bargaining power, such as females and non-household heads.

Tanzania is a perfect setting to test the relationship between different saving practices and entrepreneurial investment decisions. Tanzania is a low-income country in East Africa, whose private sector is dominated by micro and small enterprises. While the financial sector was liberalized in the 1990s and there is a large number of formal financial institutions, access to formal financial services is very low, with only 17% of adults having a formal bank account (World Bank, 2012). Tanzania shares many characteristics with other low-income countries in Africa, including a very disperse population and a high degree of informality.

This paper relates to several distinct literatures. First of all, our study investigates the role of saving practices on business investment. Past research on finance and entrepreneurial investment has shown that entrepreneurs invest more if they expect high private returns from their investment activity (e.g. Demirguc-Kunt & Maksimovic, 1998; Johnson et al., 1998). Moreover, there are several studies investigating the impact of access to external finance on investment for microenterprises (Karlan & Zinman, 2010; Kaboski & Townsend, 2011; Attanasio et al., 2012; Banerjee et al., 2013). We add to this literature by focusing on savings patterns as additional factor explaining variation in reinvestment decisions across micro- and small entrepreneurs.

Our most important contribution is to the growing literature concerning the implications of access to different saving instruments in developing countries. There are an increasing number of studies exploring the impact of access to formal banking services on the level of savings (Pande & Burgess, 2005; Kaboski & Townsed, 2005; Dupas & Robinson, 2013a). A recent experimental study by Dupas and Robinson (2013a) shows that entrepreneurs with formal bank accounts save and invest more in their businesses than entrepreneurs who do not save in formal banks. In a companion study (Dupas & Robinson, 2013b), the authors compare the health investment performance of women saving via various informal saving instruments and find that some of them boost investment in health. Similarly Brune et al. (2013) evaluate the effect of commitment to keep savings accounts on several outcomes for Malawian cash crop farmers. We contribute to this literature by comparing the investment likelihood of formal savers with different types of informal savers such as individual savers, savers via other household members, informal savings club members and moneylenders.

Our paper also relates to the literature on barriers to saving in developing countries (see Karlan, Ratan and Zinman, 2014, for an overview). In addition to geographic, monetary and regulatory barriers, there are significant social constraints on saving behavior, partly related to the position of the entrepreneur within the household. Previous research has linked participation in informal savings clubs, such as ROSCAs, to intra-household bargaining problems (e.g., Besley et al. 1993; Anderson and Baland, 2002). Social constraints can also explain why entrepreneurs save and borrow at the same time. Critically, the literature has shown that the relative position within the household is important for saving and investment decisions. For instance, de Mel et al. (2008) show that as the decision making power of women in the household increases, returns to capital and investment for women increase as well. Ashraf (2009) in a lab experiment in Philippines documents that subjects are more likely to save the randomly allocated money in their private deposit accounts if their spouse is not aware of the money, while they prefer to consume if the spouse knows about it. Evidence from an experimental study with 142 married couples in Kenya showed that husbands increase private spending if they receive an income shock. But if their wives receive the shock they do not increase their consumption (Robinson 2011). Likewise Schaner (2013) finds that well matched Kenyan couples are more likely to use joint accounts instead of costly individual ones. Our study supports these findings by showing that members of the household who have potentially less power in decision making are less likely to turn their household savings into investments.

Unlike many other papers in this literature that implement randomized control trials (RCTs), our paper relies on cross-sectional survey data and thus faces the usual endogeneity issues. We address these concerns by using instrumental variables and by exploring the differential relationship between savings patterns and reinvestment decision across different entrepreneurial groups. Beyond these methodological differences, however, our analysis also allows a broader exploration of reinvestment decisions across different savings patterns. In addition, we realize that such savings patterns are the outcome of repeated interactions and persistent habits and are thus harder if analyse using a randomized control trial.

The rest of the paper is organized as follows. Section 6.2 presents a theoretical model to show how saving practices can influence entrepreneurial investment decisions. Section 6.3 discusses the regression set-up and the set of control variables. Section 6.4 presents the data we use for our analysis. Section 6.5 discusses our main findings, while section 6.6 discusses the determinants of saving choice, tests for reverse causality and studies sub-sample heterogeneity concerning our key estimation results. Section 6.7 concludes.

6.2 Model

We develop a partial equilibrium heterogeneous firm model to study how informal entrepreneurial savings practices for business purposes (as opposed to formal saving practices) may interact with the reinvestment likelihood.[73] Parallel to our research question and the reinvestment and saving practice variables that we use in the empirical specification in section 6.3 (see below), we define reinvestment as directly investing some of the business profits back into the business. By this we mean that entrepreneurs do not transform earnings first into savings and then into bulky capital investments. In our model entrepreneurial heterogeneity has three dimensions: productivity, borrowing capacity, and saving practice. In the benchmark model all of the three dimensions are exogenous. We also extend the benchmark model in section 6.2.4, where we endogenize the saving practice as an entrepreneurial decision. In the following, we first present the economic environment, and the entrepreneur's maximization problem, before deriving optimal investment behavior. This allows us to obtain several empirically testable hypotheses.

6.2.1 Environment

There are two time periods, 1 and 2; a continuum of entrepreneurs indexed by i and a good - call it cash - that can be invested, saved, or consumed. Entrepreneurs have linear preferences over their life-time consumption such that

$$U_i = c_{1,i} + \beta c_{2,i} \tag{6.1}$$

where U_i is life-time utility and $c_{1,i}$ and $c_{2,i}$ are consumption levels in period-1 and in period-2 respectively. The parameter β is a discount factor. The linear preference specification is not essential for the qualitative findings of the model.

At the beginning of period-1, entrepreneurs are endowed with ω which we assume to be homogeneously distributed among all entrepreneurs in the economy. This endowment includes the net earnings in preceding, non-modelled periods. Entrepreneurs in this economy utilize these earnings, ω, as a resource to reinvest as well as consume and save for

[73] In the model we ignore the channel that not having a safe place to store your money, you make many small investments rather than in just one bulky opportunity.

business purposes. So savings do not have a direct relationship with reinvestment, but an indirect relationship - we will discuss this in detail below. Entrepreneur i decides on whether to consume, $c_{1,i}$; save cash for business purposes from period 1 to period 2, $s_{1,i}$; and reinvest in productive capital $k_{1,i}$, (e.g. inventory, machinery, building, and etc) in period-1. So the budget constraint for period-1 is

(6.2) $$c_{1,i} + k_{1,i} + s_{1,i} \leq \omega_i.$$

In period-2, entrepreneur i's technology yields $A_i k_{1,i}$ units of cash if and only if the entrepreneur is capable of injecting a minimum amount of cash $\bar{l}_2$ per unit of capital, $k_{1,i}$, to utilize the investment. Parameter A_i>1 captures the productivity heterogeneity across entrepreneurs; a high A_i can be associated with better training, education or some sort of intrinsic ability to manage a firm. $\bar{l}_2$ captures the expected liquidity needs per capital invested - for instance working finance requirements of the business which is necessary to utilize the technology. It does not affect the return on investment projects as long as it can be financed at the beginning of period-2.

Entrepreneurs can finance their liquidity need, $\bar{l}_2 k_{1,i}$ via two sources:

1. They can use *savings for business purposes*, $s_{1,i}$, at a rate ζ_i with $\zeta_i \leq 1$. In this formulation, ζ_i captures saving practice (in)efficiency of the entrepreneur. We assume that there are two general saving practice types: Formal (ζ_F) and informal (ζ_I). We suppose that $\zeta_F = 1$ with certainty, whereas ζ_I is drawn from a distribution function with $\zeta_I < 1$. The monetary costs associated with informal saving practices as opposed to formal saving practices motivate the relative inefficiency of informal saving practices. These costs include the lack of interest income through informal practices (in particular for saving with other household members and at a secret hiding place), informal taxes for the saving collected by the members of the family, kin or social network, or limited access to the savings (in particular when the entrepreneurs save via ROSCAs and informal moneylenders). The heterogeneity in informal saving (in)efficiency can be motivated, for instance, by the cross-sectional variation in within-household bargaining power, as we will discuss below. We also assume that saving

formally may involve utility losses due to social and transaction costs when compared with saving informally, and these costs may limit the use of formal saving tools. We will explain the utility costs in detail and how they will allow us to endogenize the model saving practice in section 6.2.4 below.

2. They can borrow cash in period-2, denote by $b_{2,i}$, which they should repay at the end of the period. Having limited access to finance in our developing country context, the entrepreneurs in our model can borrow up to a fraction θ_i of $\bar{l}_2 k_{1,i}$ in the financial market with no interest rate, where θ_i is an entrepreneur-specific parameter capturing the ability to raise liquidity - working capital - externally.[74] The borrowing capacity θ is drawn from a distribution function at the beginning of the period-1, and is publicly observable. Hence, the borrowing constraint associated with working capital finance can be shown via following inequality

$$b_{2,i} \leq \theta_i \bar{l}_2 k_{1,i}. \tag{6.3}$$

To summarize, the constraint that ensures that there is sufficient liquidity at the beginning of the period-2 - financed by saving for business purposes ($s_{1,i}\zeta_i$) and borrowing ($b_{2,i}$) - is

$$\bar{l}_2 k_{1,i} \leq s_{1,i}\zeta_i + b_{2,i}. \tag{6.4}$$

Utilizing the condition imposed by (6.4), we can summarize the entrepreneurial output at the end of the period-2, $y_{2,i}$, as follows:

$$\begin{aligned} y_{2,i} &= A_i k_{1,i} + s_{1,i}\zeta_i + b_{2,i} \quad if \;\; s_{1,i}\zeta_i + b_{2,i} \geq \bar{l}_2 k_{1,i} \\ &= s_{1,i}\zeta_i + b_{2,i} \qquad\qquad\quad if \;\; s_{1,i}\zeta_i + b_{2,i} < \bar{l}_2 k_{1,i}. \end{aligned} \tag{6.5}$$

(6.5) shows that if and only if the expected liquidity needs in period-2 can be financed, the output available to entrepreneur i includes extra cash generated by the technology, $A_i k_{1,i}$, in addition to net savings for business purposes, $s_{1,i}\zeta_i$ carried from period-1 to period-2,

[74] We do not take into consideration that borrowing capacity may be dependent on the amount of savings - the entrepreneur can use savings as collateral for bank finance -, as our focus is on saving practice and reinvestment relationship.

and borrowings $b_{2,i}$ in period-2.[75] Hence, in this economy, firms must have the capacity to manage liquid reserves in order to be able to undertake productive investment opportunities[76], and savings for business purposes have an indirect impact on reinvestment through liquidity needs.

Finally,

$$c_{2,i} + b_{2,i} \leq y_{2,i} \tag{6.6}$$

is the budget constraint for period-2 and implies that entrepreneurs use $y_{2,i}$ to consume or repay borrowed cash in period-2.

As a final remark concerning the environment, we would like to note that in this model the exact timing of k investment is not essential. All we need is that k is invested before the liquidity injection is made. This means allowing parts of the saving for business purposes s to finance k will not alter the qualitative properties of the model that we highlight in section 6.2.3.

6.2.2 Optimizing behavior

The decision variables in this model are $c_{1,i}$, $c_{2,i}$, $k_{1,i}$, and $s_{1,i}$. Entrepreneurs maximize life-time utility in (6.1) subject to budget constraints (6.2) and (6.6). An immediate implication of this model can be summarized in the following:

Lemma 6.1: *The entrepreneur sets $k_i > 0$ if and only if he has sufficient capacity to finance his liquidity needs in the second period.*

The rest of the qualitative properties of the model are as follows. Entrepreneurs who choose a $k_{1,i} > 0$ exhaust their borrowing limit, θ_i. This is implied by the assumption that

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[75] This type of a production function specification has been previously utilized in finance and development literature by Aghion et al. (2010). In their dynamic general equilibrium model, the authors introduce a complementarity between the ability to cope with future liquidity needs and current long-term investment and explain the negative correlation between volatility and growth observed in cross-country data.

[76] We assume that $\bar{l}_2$ is a common parameter among all firms in the economy. The qualitative features of the model would remain identical if we assumed heterogeneity and stochasticity in liquidity demand.

saving is inefficient ($\zeta_i < \zeta_F = 1$) in this economy for informal type of saving practices and borrowing is free.[77] Therefore,

(6.7) $$\theta_i \bar{l}_2 k_{1,i} = b_{2,i},$$

as long as $\zeta_i < 1$.

Using (6.4) and imposing equality, we get:

(6.8) $$s_{1,i} = \frac{(1-\theta_i)}{\zeta_i} \bar{l}_2 k_{1,i}.$$

Equation (6.8) implies that the lower ζ the higher is the savings for business purposes - for those entrepreneurs who choose to invest. But, as we show below a low ζ_i implies a low likelihood of earnings retention and as a result a low likelihood of saving for business purposes.

Using (6.8) in budget constraints (6.2) and (6.6) yield:

(6.9) $$c_1 = \omega_i - k_{1,i} - ((1-\theta_i)/\zeta_i)\bar{l}_2 k_{1,i},$$

(6.10) $$c_2 = A_i k_{1,i} + (1-\theta_i)\bar{l}_2 k_{1,i}.$$

By using (6.9) and (6.10), we derive the idiosyncratic rate of return from postponing consumption from period 1 to period 2

(6.11) $$\rho_i = (A_i + (1-\theta_i)l_2)/(1 + \bar{l}_2\,((1-\theta_i)/\zeta_i)),$$

which is the unit rate of return from undertaking an investment project for an entrepreneur.

Combining (6.1) and (6.11), we find that the optimal consumption plans implied

$$c_{1,i} > 0, c_{2,i} = 0 \text{ if } \rho_i < 1/\beta,$$

[77] If we introduce an interest rate for borrowing, r to the model, as long as it satisfies $r < 1 - \zeta_i$ the implications and solution of the model do not change.

(6.12) $$c_{1,i} = 0, c_{2,i} > 0 \text{ if } \rho_i > 1/\beta.$$

The entrepreneurs with a sufficiently high net rate of return on their investment (that is, $\rho_i > 1/\beta$) invest in their projects and consume the investment returns at the end of the period-2. When ρ_i is lower than $1/\beta$, the entrepreneur does not invest and consumes the endowment ω at the end of the period-1.

6.2.3 Theoretical predictions of the model

A high ρ_i increases the likelihood that an entrepreneur will reinvest. This leads to the following key empirically testable implications of the model as in the following proposition:

Proposition 6.1: *Entrepreneurs with an efficient saving practice (high ζ_i) are more likely to invest.*

Proof: Taking the partial derivative of ρ with respect to ζ we can see that

$$\partial\rho/\partial\zeta = (1/\zeta_i^2)\left[\frac{\left(\bar{l}_2\,(1-\theta_i)\left(\mathrm{A_i} + (1-\theta_i)\bar{l}_2\right)\right)}{\left[1 + \bar{l}_2\left(\frac{1-\theta_i}{\zeta_i}\right)\right]^2}\right] > 0$$

■

That the (in)efficiency of an entrepreneur's saving practice raises the likelihood of earnings reinvestment will be the key hypothesis of our empirical analysis. However, we also provide the following two testable propositions.

Proposition 6.2: *Entrepreneurs with a high borrowing capacity (high θ_i) are more likely to invest.*

Proof: Defining $z_i \equiv \left(\frac{1-\theta_i}{\zeta_i^2}\right)$ and taking the partial derivative of ρ in (6.12) with respect to θ:

$$\partial\rho/\,\partial\theta = \frac{\frac{\bar{l}_2}{z_i}\,(A_i - 1)}{\left[1 + \bar{l}_2\zeta_i z_i\right]^2} > 0$$

■

Proposition 6.3: *Productive entrepreneurs (high A_i) are more likely to invest.*

Proof: Using (6.12) we have

$$\partial\rho/\,\partial A = \frac{1}{1 + \bar{l}_2\zeta z_i} > 0$$

■

6.2.4 Endogenizing the Saving Practice

Our theoretical model implies that if an entrepreneur's saving practice is inefficient, she is induced to save a lot which makes postponing consumption from period-1 to period-2 inefficient. Therefore, an entrepreneur's saving practice is likely to be an endogenous variable, where the decision to save formally might be a costly action.

To formalize this argument, suppose that there are two saving options available for an entrepreneur as spelled out previously - formal and informal. In order to be able to save formally the entrepreneur needs to sacrifice a utility loss worth of ψ_i units of consumption for each unit of funds deposited formally. This basically implies that formal savings impose a non-monetary cost, and these costs may be type specific. The utility loss might be due to shame, fear of retaliation - if savings are discovered by family or kin - (e.g. hiding savings from family members (social network) at a bank account) or physical costs (e.g. transportation costs) as well as idiosyncratic factors.[78] These costs may be captured by age of the entrepreneur and distance to the bank. In addressing the potential reverse causation of investment on entrepreneurial saving practice in section 6.6, we use these variables as instruments.

[78] Lack of understanding how formal savings institutions work may hinder entrepreneur's access to formal savings. However we do not use them to identify the model, as they may be highly correlated with the human capital of the entrepreneur.

The efficiency of the formal saving practice is denoted with ζ_F and the efficiency of the informal saving practice is denoted with ζ_I, where $\zeta_F = 1 > \zeta_I$ for all the individuals who save informally. Using equation (6.12) from the entrepreneurial optimization problem, an entrepreneur i is willing to save formally if and only if

$$(6.13) \qquad \rho_F - \rho_I = (A_i + (1-\theta_i)\bar{l}_2)\left(\frac{1}{1+\bar{l}_2\,((1-\theta_i)/\zeta_F\,)} - \frac{1}{1+\bar{l}_2((1-\theta_i)/\zeta_I\,)\,)}\right) > \psi_i\,,$$

which would hold if (a) the entrepreneur has a low cost of accessing a formal financial institutions and/or (b) a high enough productivity and/or (c) and limited access to borrowing.

We utilize the theoretical argument we derived in equation (6.13), when we study the reverse causation of re-investment likelihood on entrepreneurial saving practice in section 6.6.

6.2.5 Impact heterogeneity

The entrepreneurial (in)efficiency associated with informal saving practice is expected to be a function of accessibility to savings. Such accessibility constraints could be related to the repayment structure for the case of informal saving networks (e.g. Rotating-Saving-and-Credit-Associations) and within household bargaining power for the case of in-household savings. This implies, for instance, that entrepreneurs with low household bargaining power would have a lower ζ_I. The bargaining power of an individual could vary according to the position of the individual in the household in developing country contexts. Because of social norms and pressure, for instance female household members and children are naturally at a more disadvantageous position than males and household heads in terms of claiming from the common resources of the household. They are less likely to claim money from the common savings pot of the household to finance their liquidity needs thereby reinvesting less likely. We will utilize this intuition in our sample-split empirical analysis while studying impact heterogeneity in section 6.6.

6.2.6 Empirically testable hypothesis

In our regression equations we will control for a vector of variables to test the empirical fit our model to the data based on the theoretical results we obtained in propositions 1 through 3. Specifically, the empirically testable hypotheses resulting from our model as the following:

1. H_0: Entrepreneurs who can save efficiently (high ζ), - saving formally in a formal bank account, MFI or savings cooperatives as opposed saving informally - are more likely to reinvest.
2. H_0: Entrepreneurs with a high borrowing capacity (high θ) – who have used external finance for business purposes - are more likely to reinvest.
3. H_0: Entrepreneurs with high productivity (high A) - with better training, higher education and higher income - are more likely to invest.
4. H_0: Entrepreneurs with high utility loss due to saving formally (low ψ) - at lower ages and living faraway from formal banking services for saving - are less likely to save formally.

6.3 Empirical methodology

To test whether saving practices affect the decision to reinvest, we use the binary outcome variable *reinvest*, which equals 1 if the entrepreneur invests some of the profits back into business and 0 otherwise, and estimate the following model:

$$\mathrm{Reinvest_i} = \alpha + \beta' \mathrm{S_i} + \gamma' \mathrm{Controls_i} + \varepsilon_\mathrm{i}, \tag{6.14}$$

where *i* denotes the entrepreneur, *S* is a vector of saving practices comprised of dummy variable(s) which take(s) the value of 1 if the entrepreneur has the corresponding saving practice (see below for details) and ε is the error term. The vector of control variables included in the benchmark model is composed of an array of entrepreneurial and enterprise characteristics that we discuss in the following.

First, in line with our theoretical model, we control for firms' ability to borrow. Specifically, *Borrowed* is a dummy variable which takes the value of 1 if the entrepreneur has ever borrowed to cover business needs, and this is a proxy for the θ_i parameter in the theoretical model. Businesses that have access to external finance are expected to reinvest more frequently even in the absence of regular entrepreneurial savings.

Second, we use income level, education and business training history of entrepreneurs as proxies of entrepreneurial productivity A_i . We conjecture that entrepreneurs with a higher *household income* can save more and as a result reinvest more often. To control for the entrepreneur's income, we use self-reported monthly personal income levels.[79] Entrepreneurs with high levels of human capital are expected to be more committed to business growth, and to have higher rates of earnings retention. We therefore use the highest level of *formal education* completed by the respondents, as well as an indicator of entrepreneurial training, as this should matter for expected business performance and reinvestment behavior.

Third, although they are not discussed in our model, we additionally control for *gender* and *marital status* as previous studies showed that both can influence investment decisions (Iversen et al., 2006; Ashraf, 2009; de Mel et al., 2009 and Fafchamps et al., 2013). Specifically, we expect female entrepreneurs to face more claims on their income from spouse and family members. Similarly, married entrepreneurs might face more claimants on the business profits and might therefore be less likely to re-invest. Finally, we include sectoral dummies to control for sectoral performance that might explain reinvestment heterogeneity, as well as regional dummies to control for geographic heterogeneity in profitability and reinvestment.

Our survey allows us to identify two types of saving practices among Tanzanian entrepreneurs which we classify as follows:

1. *Save formal*: This practice includes the entrepreneurs who save their funds at formal financial institutions such as commercial banks, microfinance institutions or saving & credit cooperatives. The entrepreneurs who save only formal and save both

[79] Each respondent is asked which income range (e.g. TSHS 35 001 - TSHS 40 000 per month) describes their income level best. We use the median of that range (e.g. TSHS 37500.5) as the income level of the respondent.

formal and informal (please see below for the definition) are considered in this group.

2. *Save informal*: We consider entrepreneurs who do not save formally in this group.

Yet, our survey allows a finer classification to exploit the considerable heterogeneity in terms of informal saving practices. Therefore we first divide *save informal* into two groups and distinguish individual saving practices and practices involving interaction with other people as follows:

1. *Save informal individually*: A large fraction of entrepreneurs in Tanzania save their funds only in a secret hiding place or piggy bank.[80] We classify this behaviour as "informal individual saving" practice.

2. *Save informal with others*: We classify the practices of saving funds via informal savings clubs, such as ROSCAs, or moneylenders or within household savers under "saving with others". We do not include respondents who also save formally in this group.[81]

To distinguish whether our entrepreneurs save through people living in the household or people who are not member of a household, we decompose the practice of "*Save informal with others*" further into two groups.

1. *Save with household members*: The group comprises entrepreneurs who give their funds to other household members for safe keeping.

2. *Save with people outside household*: The group contains entrepreneurs who save through ROSCAs or moneylenders. The entrepreneurs who both save informal with household members and save informal with people outside household are considered in this group.[82]

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[80] Piggy bank is a coin container.

[81] Our results are robust when we create a separate dummy variable for this group having both saving practices and add them to the regressions.

[82] We do not include this group having both practices save informal both with people outside household and with household members to our main regression specifications as only a few respondents (7) have both practices.

We again conjecture that entrepreneurs in the second group have more control over their savings than entrepreneurs in the first group, especially if the latter have limited intra-household bargaining power. In our regression analysis, we will use a dummy variable for each saving practice above (see Table 6.1 below for the descriptions) and work with different samples to compare both savers and non-savers but also different groups of savers in their reinvestment behaviour.

6.4 Data

The dataset is based on a novel enterprise survey conducted at the MSE-level in Tanzania. The survey data was collected by the Financial Sector Deepening Trust Tanzania in 2010 from a nationwide representative cross-section of 6,083 micro- and small enterprises. The respondents of the questionnaire are entrepreneurs with an active business as of September 2010. Table 6.1 presents both detailed definitions of the variables and descriptive statistics of the sample.

The descriptive statistics in Panel A of Table 6.1 shows that the average number of employees among Tanzanian MSEs is 1.5 workers, ranging from one (i.e. self-employed) to 80 employees.[83] However, 97% of entrepreneurs are self-employed. The median initial capital is about 35 USD and average monthly sales are 149 USD. The key question which we exploit to capture entrepreneurs' earnings retention asks whether *the respondent reinvests some of the profits back into business*. As presented in Table 6.1, 76% of the sample entrepreneurs engage in earnings retention.

The sectoral breakdown in Panel B of Table 6.1 exhibits substantial variation: 54% and 30% of the businesses operate in the trade and service sectors, respectively, while 15% of enterprises operate in manufacturing.

Panel C of Table 6.1 presents characteristics of entrepreneurs and enterprises. About 50% of the entrepreneurs in the sample are female, 10% of the entrepreneurs are single. 30% of the sample entrepreneurs received business related training, and about 87%

[83] The relationship between business owners' saving and re-investment decisions might be weak in large businesses because of managerial layers. We test the robustness of our main result by excluding the businesses larger than 10 from our sample. Estimates reported in Table 6.3 do not change.

of the entrepreneurs have less than completed secondary education. 75% of the enterprises are located in rural areas. The median monthly personal income of entrepreneurs is 106 USD.[84]

Table 6.1: Descriptive statistics for the main variables

Panel A: Firm characteristics	**Description**	**Obs**	**Mean**	**S.D.**	**Min**	**Max**
Reinvestment	Equals to 1 if respondent re-invest some of the profit back to business, 0 otherwise	6083	0.76	0.43	0	1
Employee	Number of employees business has (including owner)	6083	1.47	1.61	1	80
Initial capital	Logarithm of initial capital of the business, in Tanzanian Shillings	6083	10.62	2.21	0	25.33
Panel B: Sectoral breakdown of firms	**Number of companies**	**%**				
Trade	3291	54.1				
Service	1841	30.3				
Manufacturing	931	15.3				
Other	20	0.3				
Panel C: Entrepreneur characteristics	**Description**	**Obs**	**Mean**	**S.D.**	**Min**	**Max**
Education	Education level of the respondent, (0 none-6 university)	6077	2.00	0.89	0	6
Female	Equals to 1 if respondent is female, 0 otherwise	6083	0.50	0.50	0	1
Single	Equals to 1 if respondent is single, 0 otherwise	6083	0.10	0.29	0	1
No training	Equals to 1 if respondent has no business related training, 0 otherwise	6083	0.70	0.46	0	1
Rural	Equals to 1 if respondent lives in a rural area, 0 otherwise	6083	0.75	0.44	0	1
Income	Logarithm of personal income level of the respondent in Tanzanian Shillings	5868	11.94	1.15	9.90	15.20
Bank branch within one hour walking distance	Equals to 1 if there is a bank within a one hour walk from the home of the respondent, 0 otherwise	6083	0.30	0.46	0	1
Min. distance to ATM, bank branch, or MFI	Minimum distance of the ward entrepreneur lives to the nearest ATM, bank branch or MFI, in logarithms, at ward level)	583	2.04	1.78	-4.35	6.12
Age	Age of the respondent	6083	36.84	10.58	16	91

[84] This is computed with the average exchange rate for 2010. If using PPP exchange rates, the corresponding median income would be 288 dollars.

Table 6.1 (continued): Descriptive statistics for the main variables

Panel D: Finance variables	Description	Obs	Mean	S.D.	Min	Max
Save	Equals to 1 if respondent saves for business purposes, 0 otherwise	6083	0.77	0.42	0	1
Save formal	Equals to 1 if respondent saves in a bank account, MFI or SACCO, 0 otherwise	6083	0.10	0.30	0	1
Save informal	Equals to 1 if respondent saves but not in a bank account, MFI or SACCO and, 0 otherwise	6083	0.67	0.47	0	1
Save informal individually	Equals to 1 if respondent saves in a secret hiding place or piggy bank and does not save via other means, 0 otherwise	6083	0.57	0.49	0	1
Save informal with others	Equals to 1 if save informal with household members or save informal with people outside household equals to 1 and respondent does not save formally, 0 otherwise	6083	0.10	0.30	0	1
Save informal with household members	Equals to 1 if respondent save via by giving it to a household member to keep it safe and does not save formally, 0 otherwise	6083	0.06	0.24	0	1
Save informal with people outside household	Equals to 1 if respondent save via by giving it to a non household member or merry go-round and does not save formally, 0 otherwise	6083	0.05	0.2	0	1
Borrowed	Equals to 1 if respondent has ever taken a loan/ borrowed money for business purpose, 0 otherwise	6083	0.18	0.38	0	1
Formal loan	Equals to 1 if respondent took a to set up or take over the business from a bank or MFI, 0 otherwise	6083	0.03	0.16	0	1
Semi-formal loan	Equals to 1 if respondent took a to set up or take over the business from an employer, SACCO, Village Bank, local government schemes or donor/NGO, 0 otherwise	6083	0.02	0.13	0	1
Informal loan	Equals to 1 if respondent took a to set up or take over the business from family, friends, savings club, money lender or supplier, 0 otherwise	6083	0.06	0.24	0	1

Panel D of Table 6.1, finally, presents our variables and descriptive statistics on the financing patterns of enterprises in our sample. Only 18% of all sample entrepreneurs ever borrowed for business purposes; 3% of entrepreneurs in the sample borrowed from a bank or MFI, 2% borrowed from a semi-formal financial institution, such as a SACCO or village bank and 6% borrowed from an informal source, such as money lenders, savings club or family and friends.

Saving is a common habit among the entrepreneurs in our sample. We utilize an extensive margin question asking whether the entrepreneur saves for business purposes, and distinguish savers from the rest of the population: 77% of the entrepreneurs in the sample save for business purposes. However there is considerable heterogeneity among saving practices of Tanzanian entrepreneurs. Informal individual saving is the most wide spread practice among Tanzanian entrepreneurs. 75% of the savers save informal-individually whereas around 13% of them save formally. Likewise, 13% of the savers do not save at a formal financial institution and instead save their funds via people outside the household such as members of ROSCAs and moneylenders, or give the savings to household members.

Table 6.2 presents a correlation matrix concerning the variables of interest for our analysis. The key variables such as "being a saver" and "retaining earnings within the business" exhibit a strong correlation. However, the sign of the relationship seems to be dependent on the saving practice of the respondents. In particular saving via others seems to be negatively correlated with firm reinvestment whereas formal and informal individual savers have higher reinvestment rates. We also note a high correlation among other firm characteristics, such as borrowing and saving activity.

Table 6.2: Correlation Matrix: Pairwise correlations among selected variables

	Reinvestment	Save	Save formal	Save informal individually	Save informal with others	Save with other household members	Save with people outside household	borrowed	education	female	single	notraining	income
Reinvestment	1.00												
Save	0.09*	1.00											
Save formal	0.07*	0.18*	1.00										
Save informal individually	0.05*	0.62*	-0.38*	1.00									
Save informal with others	-0.03*	0.18*	-0.11*	-0.39*	1.00								
Save with other household members	-0.04*	0.14*	-0.08*	-0.29*	0.74*	1.00							
Save with people outside household	0.00	0.12*	-0.07*	-0.25*	0.64*	-0.03*	1.00						
Borrowed	0.06*	0.12*	0.30*	-0.09*	0.03*	-0.01	0.05*	1.00					
Education	0.07*	0.13*	0.24*	-0.04*	0.02	0.02	0.01	0.17*	1.00				
Female	-0.06*	0.00	-0.05*	0.03*	0.00	-0.10*	0.11*	0.03*	-0.10*	1.00			
Single	0.02	0.00	0.00	0.01	-0.01	0.00	-0.01	-0.04*	0.07*	0.01	1.00		
No training	-0.02	-0.06*	-0.08*	0.02	-0.04*	-0.04*	-0.01	-0.10*	-0.12*	0.00	0.00	1.00	
Income	0.13*	0.12*	0.19*	-0.02	0.01	0.02	-0.02	0.12*	0.19*	-0.24*	-0.02	0.00	1.00

* Significant at least 5 percent level

6.5 Saving practices and reinvestment: Baseline results

Since our dependent variable is binary, we estimate probit models for all different specifications of (6.14), and report marginal effects at mean levels for the coefficient estimates unless we state otherwise. Table 6.3 reports those marginal effects for the benchmark regression. We use heteroscedasticity robust standard errors and report the standard deviations associated with coefficient estimates in parentheses.

Table 6.3: Estimates for reinvestment and saving/saving practices relationship

	(1)	(2)	(3)	(4)	(5)
Save formal	0.09*** (0.02)				
Save informal	0.06*** (0.01)	-0.04* (0.02)			
Save informal individually			-0.03 (0.02)		
Save informal with others			-0.09*** (0.03)		
Save with household member				-0.12*** (0.04)	
Save with people outside household					-0.04 (0.03)
Borrowed	0.04** (0.02)	0.05*** (0.02)	0.05*** (0.02)	0.05 (0.03)	0.04 (0.03)
Education	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Female	-0.03** (0.01)	-0.03** (0.01)	-0.03*** (0.01)	-0.07** (0.03)	-0.04 (0.03)
Single	0.04** (0.02)	0.03 (0.02)	0.03 (0.02)	0.06 (0.04)	0.03 (0.04)
No training	-0.03*** (0.01)	-0.04*** (0.01)	-0.04*** (0.01)	-0.07** (0.03)	-0.06** (0.03)
Income	0.03*** (0.01)	0.02** (0.01)	0.02** (0.01)	0.03** (0.01)	0.05*** (0.01)
Observations	5,803	4,499	4,499	877	774
Sample	All	All	Savers	Formal Savers and Household Savers	Formal Savers and Non-household Savers
Base category	Non-savers	Formal Savers	Formal Savers	Formal Savers	Formal Savers

Notes: Reinvestment is the dependent variable in the estimations. We report estimates marginal effects at mean values for all estimations and robust standard errors are in parentheses. We additionally control for sector and region dummies in the estimations. *** p<0.01, ** p<0.05, * p<0.1.

The results in the first column show that the probability of reinvestment is higher for both groups of savers compared to non-savers. Specifically, ceteris paribus, the reinvestment probability of an average Tanzanian MSE who saves informally is around six percentage points higher than for an entrepreneur who does not save, while the reinvestment probability of an average Tanzanian MSE who saves formally is around nine percentage points higher. We also find that entrepreneurs with access to formal loans are more likely to reinvest, while formal business training increases the likelihood of reinvestment in business projects. Female and married entrepreneurs are less likely, while richer entrepreneurs are more likely to invest. Overall, these results are consistent with our theoretical predictions as discussed above and the existing literature.

Our empirical analysis, so far, stresses the significance of *entrepreneurial savings* to foster entrepreneurial reinvestment in business projects and we confirmed that saving related correlations are in line with the findings in the literature. In the next step, we focus on our main research question and we deepen our analysis by studying the implications of saving *practices* on reinvestment. In order to test the predictions from our theoretical model, we rank saving *practices* based on their vulnerability to consumption temptations - as we discussed above - and investigate the implications of the variations in saving methods for the probability to reinvest. Specifically, we rank the "within household savers" as the group for whom the vulnerability to consuming savings is the highest. On the other extreme, we expect the most committed savers to be "formal savers" due to the highest opportunity cost of consumption - resulting from the foregone interest income. Finally, comparing "informal individual savers" with "informal savers with others", we conjecture that while the redistributive pressure problem might be lower for the former, there would be a potential inflexibility to withdrawing savings when needed associated with the latter.

Here we also note that we study our main research question by focusing on specific sub-samples of savers in order to present the results clearer, and keep the consistency between the samples used for main estimations, robustness checks and bivariate probit estimates (see below). To show that our estimates are not biased due to this method, we replicate the analysis by using the entire sample. We present the results in Table A.6.1 in the Appendix, and show that our estimates are robust.[85]

The results in column 2 show that "formal savers" are four percentage points more likely to retain earnings than the "informal savers". To investigate the effects of individual saving practices on earnings retention we limit our sample to savers and thus drop respondents who do not save. The results in column 3 show that entrepreneurs that save with others are less likely to reinvest than entrepreneurs that save formally.[86] Also, entrepreneurs who save informally but individually are not significantly less likely to reinvest when compared to "formal savers".

Finally, we focus on the group of respondents who save with others. We independently study the investment likelihood of household savers and respondents who save outside the household compared to the reinvestment probability of formal savers. The regression in column (4) keeps only formal savers and household member savers in our sample, while the regression in column (5) keeps only formal savers and outside household savers in our sample. In both cases, we gauge the difference in reinvestment behaviour relative to formal savers. Therefore, the total numbers of observations in these two regressions are 877 and 774, respectively. Confirming our conjecture, we cannot reject the null hypothesis that "with household member savers" reinvest less frequently compared to "*formal savers*", at the 5% level. Furthermore, we also show that, although the coefficient estimate of *Save with people outside household* variable in the last regression is not significant, the negative coefficient sign is consistent with the argument that the inflexible withdrawal opportunity of "informal savings" might be a barrier to earnings retention.

In summary, our baseline empirical results are consistent with our theoretical model showing that inefficient saving practices lead to a lower likelihood of reinvestment, and

[85] The only difference between the results concerns the estimate for saving with people outside the household. It is statistically significant at ten percent level due to lower standard error estimates when we use the full sample.

[86] Here we consider entrepreneurs who have both types of informal saving practices, "saving informal individually" and "saving informal with others" inside "save informal with others" group. When we estimate specification in column-3 by adding a separate dummy for individuals having both practices and saving only informal with others together saving informal individually, estimates for the first two groups including saving practices with others are negative and statistically significant showing that our results are robust.

hence also a lower likelihood of earnings retention. It is important to note that this finding is mainly driven by the difference in the reinvestment likelihood between within household savers and formal savers, for which the difference is most pronounced and statistically significant. The entrepreneurs who save informally with household members are around 12 percentage points less likely to reinvest than entrepreneurs saving formally in a bank or MFI account.

In Table 6.4, we test the robustness of our key result concerning the difference in reinvestment likelihood between formal and within household savers (see column (4) in Table 6.3) with respect to the inclusion of a vector of additional control variables. First, we add specific dummy variables for different sources of external finance at the start-up of the enterprise: formal, semi-formal and informal loans. Our indicator for external finance may not capture the potential implications of access to different sources of finance for reinvestment decisions. Getting loans from a formal financial institution might require a bank account and facilitate formal entrepreneurial savings. However, none of the external financing variables that we include have significant explanatory power regarding the likelihood of reinvestment. Second, we control for *entrepreneurial types* by utilizing the answers of to the following survey question: "*why did you go to business?*"[87] As evidenced in the previous literature (Bruhn & Zia 2013), transformational type entrepreneurs are expected to have higher rates of investment profitability and earnings retention rate compared to survival type entrepreneurs. While we do not report the individual dummy variables, some variables enter significantly at the 5% level. Third, we add dummy variables to control for the type of the activity the business conducts. The activity of the business (e.g. buying and re-selling; buying, adding value and re-selling, providing a service etc.) may change the definition of reinvestment for business owners and also the timing of the reinvestment. For instance, they may be different for a restaurant owner than for a market vendor. To control for this factor, we include answers to the question "what

[87] Entrepreneurs selected from a list of statements to indicate why they went into business. Multiple choices were available. The answers include: I was fired / lost/retrenched from a previous job; I couldn't find a job elsewhere; To support me / my family; To try out a business idea; I believe I can make more money working for myself than for someone else; I had nothing else to do/no other means of survival/no better option; parents / relatives were in business; I saw a good opportunity; I have always wanted my own business; I was encouraged by friends and relatives; I needed to supplement my income; Others, please specify.

does your business do?" as dummy variables.[88] The estimates for the variables are jointly significant at the 1 percent level. To economize on space we do not report estimates, and they are available upon request. Fourth, we include the size of the logarithm of the initial start-up capital, the logarithm of current sales per employee, the logarithm of duration business and the logarithm of number of workers since these size gauges are expected to determine the growth potential of a business- and hence the profitability of reinvestment. We also control for rural versus. urban location of the enterprise, as the accessibility to infrastructure might affect expectations and drive variations in reinvestment rates. Including all of these control variables does not affect our key empirical finding.

Table 6.4: Robustness checks for reinvestment and save with household member relationship

	(1)	(2)
Save with household members	-0.07**	-0.18***
	(0.03)	(0.05)
Formal loan	0.02	
	(0.05)	
Semi formal loan	-0.11	
	(0.09)	
Informal loan	-0.12	
	(0.07)	
Initial capital	0.02**	
	(0.01)	
Sales per worker	-0.02	
	(0.01)	
Rural	0.03	
	(0.03)	
Size	0.04	
	(0.03)	
Duration	0.02	
	(0.01)	
Observations	872	650
Entrepreneurial dummies	Yes	No
Activity Dummy	Yes	No
Region FE	Yes	No
District FE	No	Yes

Notes: Reinvestment is the dependent variable in the estimations. We report estimates marginal effects at mean values for all estimations and robust standard errors are in parentheses. We use the sample for Formal Savers and Household Savers and formal savers as the base category. We additionally control for sector and region dummies in the estimations. *** p<0.01, ** p<0.05, * p<0.1.

[88] We include 4 separate dummy variables for the businesses buying and selling goods; buying, adding value and selling goods; making and selling goods; providing service; and other activities including agricultural ones.

Finally, in column (2) we replace the region fixed effects with district fixed effects to ensure that we are capturing geographical variations well enough that could explain the probability of reinvestment. While our sample becomes smaller, our findings remain.[89]

6.6 Saving choice, reverse causality and heterogeneity

While controlling for other enterprise and entrepreneurial characteristics reduces the risk that the relationship between savings patterns and the likelihood of reinvestment is a spurious one, we cannot exclude the possibility that our relationship is driven by other sources of endogeneity, including reverse causation. As we show in our theoretical model, entrepreneurs who are more willing to reinvest might look for saving practices that support their investment efforts. In the following, we focus on the sample of formal and within-household savers once more since our key result from the empirical analysis of section 6.5 is that "within household savers" are less likely to re-invest than "formal savers". Focusing on only one sub-sample also has a methodological advantage as we need fewer exogenous determinants to identify the relationship. For this sample, we investigate the relationship between entrepreneurial saving choices and characteristics, and then offer tests to alleviate endogeneity concerns.[90]

To investigate the determinants of saving choice, we replace the dependent variable *reinvest* with *save within household* in (14) and regress it on our list of control variables as well as on two additional measures denoted by ψ_i in our theoretical model: Age of the entrepreneur and distance to bank. Age increases the bargaining power of the entrepreneur within the household and this implies a U-shaped relationship between age and the choice within household saving. On the one hand, agents are less likely to be forced to save within household as they get older. On the other hand, when they reach an age giving them enough power to protect their savings within the household, they may be more likely to

[89] Note that when we include district fixed effects the total number of observations in the regression decreases to 650 because some districts are excluded from the regression in Probit estimations due to perfect prediction. Our estimates are robust when we estimate the same model with OLS and do not lose any observations.

[90] Using age as an instrument may be problematic if age has a direct impact on investment decision (e.g.older agents may be less likely to invest their business) However, our test results (see below) show that age does not have an impact on reinvestment decision if it is included into the model together with saving choice variables..

save with household members. The distance to the nearest bank is expected to increase accessibility of "formal savings services". We estimate two models with two different measures of distance to formal financial institutions. The first one is a subjective distance measure constructed by using the question from the survey: Is there any bank branch in one hour walking distance to your house? However, there might be a concern regarding the subjective measure, as entrepreneurs who search for formal savings instruments are also those who are more likely to know of the existence of a bank in the close proximity. Therefore, the correlation between the search intensity and some unobserved characteristics may bias our results. For this reason, we estimate a model with an additional objective distance measure, the logarithm of ward level minimum distance to the closest bank branch, MFI or ATM in 2013 which we constructed using data from the Financial Services Map.[91]

Table 6.5 reports the marginal effects from probit estimations for the saving practice choice. In columns (1) and (2) we present the results for models including subjective and objective measures respectively. As we conjecture, the likelihood of saving with household members is higher when entrepreneurs are closer to banks. Moreover, as the age of the entrepreneur increases, he or she is less likely to save with household members. The positive coefficient (0.00038) on the square of age indicates that the age saving with household members practice relationship is non-linear and U-shaped. As the age of the entrepreneur increases, the impact of the age on the saving practice decreases, and getting older increase the probability of saving with household members after the age of 52. The rest of the estimates are also in line with theory. Entrepreneurs who have access to external finance and entrepreneurs with higher education, better training or high income are more likely to save formally. Finally, female entrepreneurs seem more likely to save in formal institutions - perhaps to escape from redistributive pressures. Also, non-married entrepreneurs are more likely to save formally.

[91] We use data from the Financial Services Map for Tanzania. This data set gives geographic coordinates of bank branches, MFIs and ATMs in 2013 across Tanzania. We match these data with the existing geographic coordinates of the wards from which entrepreneurial data are collected. Then we calculate the distance of the wards to each financial unit and pick the minimum distance.

Table 6.5: The relationship between individual and business characteristics and saving choice

	(1)	(2)
Bank branch within one hour walking distance	-0.13***	
	(0.04)	
Min. distance to ATM, bank branch, or MFI		0.04***
		(0.01)
Age	-0.04***	-0.04***
	(0.01)	(0.01)
Age^2	0.00***	0.00***
	(0.00)	(0.00)
Borrowed	-0.32***	-0.32***
	(0.03)	(0.04)
Education	-0.12***	-0.12***
	(0.02)	(0.03)
Female	-0.10**	-0.10**
	(0.04)	(0.04)
Single	-0.14**	-0.14*
	(0.06)	(0.07)
Notraining	0.02	0.01
	(0.04)	(0.04)
Income	-0.10***	-0.10***
	(0.02)	(0.02)
Observations	877	797

Notes: Save with household member is the dependent variable in the estimations. We report estimates marginal effects at mean values for all estimations and robust standard errors are in parentheses. We use the sample for Formal Savers and Household Savers and formal savers as the base category. We additionally control for region dummies in the estimations. *** p<0.01, ** p<0.05, * p<0.1.

To circumvent the endogeneity concerns, we use an instrumental variable methodology which makes use of the determinants of saving practice choice. Since our dependent and main explanatory variables are binary, we use a system approach, and utilize the age of the entrepreneur and her distance to the nearest bank as instruments in a nonlinear recursive bivariate probit model.[92] Specifically the model is formulated as follows:

[92] We also estimate the same model by using the 2SLS method. We have the same expected signs for the variables of interest but the coefficient estimates are bigger and imprecise as the variance increases. This may be because both the dependent and independent variables of interest are binary. Chibus et al. (2012) suggests

(6.15) $\mathrm{Reinvest_i} = \phi + \delta * \mathrm{Savehousehold_i} + \eta'\mathrm{Controls_i} + \sigma_i,$

(6.16) $\mathrm{Savehousehold_i} = \lambda + \varphi'\mathrm{Z_i} + \pi'\mathrm{Controls_i} + \mathrm{u_i}.$

We assume that error terms σ_i and u_i are distributed via bivariate normal distribution. So, $E[\sigma_i] = 0$, $E[u_i] = 0$ and $cov[\sigma_i, u_i] = \mu$. We identify the system by using the vector *Z* which includes the distance to bank measure and age of the entrepreneur as well as its square and use a similar set of controls as in the main specifications.[93] Table 6.6 shows the results. Before presenting the estimates of the bivariate probit model, in columns (1) and (2), we test in unreported regressions the exogeneity of our instruments. As standard over identification tests for 2SLS are not available for Bivariate Probit estimation, we utilize an informal test procedure commonly used in the empirical literature (e.g. Egger et al., 2011; Booker et al., 2013): We introduce the instruments into the benchmark model and show that none of the instruments has explanatory power for the probability to reinvest. We also test the joint significance of our exogenous variables in the bivariate probit model: they are jointly significant at the 1 percent level (Chi-square>20 and p-value<0.001 for both specifications). In columns (3) and (4) we present the recursive bivariate-probit estimates by using age in both models, but two different distance measures as our instruments. Also, Table A.6.2 in the Appendix shows detailed estimation results for the model, including the control variables.

The instrumental variable estimations reported in columns (3) and (4) of Table 6.6 confirm our results. The coefficient estimate of *save with household member* remains negative and significant for both instrument sets. Different measures of distance produce similar results thereby minimizing the concerns regarding the validity of the distance-to-bank proxies. We also note that the estimates for the exogenous variables have the expected signs. The probability to save in the household decreases as the proximity to bank decreases and entrepreneur gets older. We have also important evidence minimizing the endogeneity concerns: The estimated cross correlation coefficient, $\hat{\mu}$, is not statistically

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2SLS may give very different results and imprecise estimates if the number of observations is lower than 5000 (in our case it is 877).

[93] We do not use sector dummies in the bivariate probit estimations since our model does not converge. However, not using sector dummies does not change our results since our main results shown in Table 6.3 are robust when we do not control for them.

significant in both estimations, so we do not reject the null hypothesis that σ_i and u_i are uncorrelated and $Reinvestment_i$ *is exogenous* for saving practice choice shown by (6.16).

Table 6.6: Exogeneity of instruments and estimate for save with household members by using bivariate probit

	Exogeneity checks		Bivariate Probit Estimates	
	(1)	(2)	(3)	(4)
Save with household member	-0.11***	-0.10	-0.20**	-0.20**
	(0.04)	(0.04)	(0.10)	(0.10)
Bank branch within one hour walking distance	0.00			
	(0.03)			
Min. distance to ATM, bank branch, or MFI		-0.01		
		(0.01)		
Age	0.01	0.01		
	(0.00)	(0.01)		
Age^2	0.00	0.00		
	(0.00)	(0.00)		
$\hat{\mu}$			0.23	0.27
			(0.23)	(0.24)
Observations	877	797	877	797
Distance measure	-	-	*Bank branch within one hour walking distance*	*Min. distance to ATM, bank branch, or MFI*
Methodology	Probit	Probit	Bivariate Probit	Bivariate Probit

Notes: We report estimates marginal effects at mean values for all estimations. We report robust standard errors for columns 1 and 3 and clustered robust standard errors at ward level in columns 2-4 in parentheses. We use the sample for Formal Savers and Household Savers and formal savers as the base category We additionally control for variables introduced above and region dummies in the estimations. *** p<0.01, ** p<0.05, * p<0.1.

As a final robustness check, we control for Rural dummy (equals to if the entrepreneur lives at a rural area), which is correlated with distance to bank measures, in our bivariate probit estimations. We do not report estimation results to economize on space and they are available upon request. The coefficient estimates for “Save with household members” are robust, and Rural has no explanatory power for reinvestment in both Bivariate Probit models. However distance to bank measures predicting Save informal with household members are not statistically significant in the estimation. These findings may imply that the entrepreneurs living at rural areas save through household members since they have limited access to banking services. Yet we cannot rule out the possibility that distance to bank may be correlated with some unobserved factors that may be correlated with reinvestment decision; we therefore should be cautious in interpreting the results.

As we discussed in section 6.2.6, we expect heterogeneous reinvestment responses with respect to the within-household saving practice. Therefore, in order to deepen our analysis and strengthen our identification, we present a set of impact heterogeneity results in Table 6.7. Specifically, we compare the reinvestment behaviour of entrepreneurs who save with household members with the reinvestment behaviour of entrepreneurs that use formal savings mechanisms across the following two sample splits. First, we split the sample into female and male entrepreneurs. Theory and empirical evidence suggests that social constraints on accessibility of saved funds are higher for women compared to men. Second, we split the sample into entrepreneurs that are household heads and entrepreneurs that are spouses, children or siblings. We expect the social constraints to be less strong for household heads.

Table 6.7: Heterogeneity in the impact of saving in the household on reinvestment

	Gender		Position in the household	
	Male	Female	Other (Child, spouse, sibling etc)	Head
Save with household member	-0.12** (0.05)	-0.22*** (0.08)	-0.22*** (0.08)	-0.16*** (0.06)
Observations	402	275	213	441

Notes: We report marginal effects at mean values for all estimations from Probit estimations and robust standard errors are in parentheses. We additionally control for control variables listed in Table 6.1 as well as sector and region dummies in all estimations. *** p<0.01, ** p<0.05, * p<0.1. The numbers of observations are less than original sample because some control variables perfectly predict outcome variables. We estimate all models for comparable subsamples where there is variation in our outcome variable with respect to control variables. We use the sample for Formal Savers and Household Savers and formal savers as the base category.

The results in Table 6.7 confirm the differential relationships between household savings and reinvestment decisions. The results reveal that the marginal effects of *Save with household members* on reinvestment are larger - and more significant - for female and non-head family members. While the negative relationship between saving within the household and reinvestment decisions are significant at least at the 10% level for all groups, the economic significance is large for female, non-household heads - female and non-head family members are respectively 10 and 6 percentage points less likely to reinvest than male and family head household members when they save informal with household members instead of saving at a formal bank account. Supporting our theoretical predictions, this result implies that entrepreneurs who are in disadvantageous positions in their households are more negatively affected from inefficient saving practices.

6.7 Conclusion

Past research has identified several factors that are important for entrepreneurial investment in developing countries. In this study, we explored how different entrepreneurial saving practices - i.e. saving via formal financial institutions, individually (under the mattress), within the household or within informal arrangements, such as ROSCAs - are related with the likelihood of reinvestment. To this end, we used a novel survey data set collected from MSEs in Tanzania and distinguished multiple saving practices of entrepreneurs as well their earnings retention behaviour. We motivated our empirical research with a simple theoretical model that shows how different saving practices can influence investment decisions. We have three key empirical results. First, we show that saving and the probability of reinvestment are significantly correlated. Second, we provide evidence that entrepreneurs who save by giving funds to other household members are less likely to reinvest than formal savers. Third, we document that the difference in the likelihood of reinvestment across saving practices is significantly higher for those entrepreneurs who potentially have low bargaining power in the household.

Our results have important implications for the interactions between enterprise performance and access to financial, in particular saving, services. Enterprises that exploit reinvestment opportunities are expected to be more likely to sustain higher productivity levels and survive more often. Access to formal bank account services in this respect could be the key to facilitate enterprise performance in financially developing societies and may increase the reinvestment likelihood up to 10 percentage points. Moreover our findings suggest that female and younger entrepreneurs are more likely to demand these services and may benefit most from the introduction of formal saving instruments in low income areas. Therefore, from a development policy perspective, targeting those entrepreneurs and facilitating their access to formal saving instruments could be thought as a priority.

We should mention two caveats. First, one may be concerned of whether our instruments are exogenous or we control for all confounding factors in the estimation. Although our main results are robust to various checks, future research using quasi-experimental variation in saving practice will be a contribution to the literature. Second we do not observe variation in intensive margin for neither the savings nor investment levels, and this may have implications on results. For instance entrepreneurs who save by inefficient means may increase their savings in intensive margin. That is there is need for future data collection concerning savings and investment levels.

Our research raises also some new issues regarding the implications of savings practices of entrepreneurs. First, why do savers inside households not open a bank account to save? Although we implicitly show proximity to banks as an important factor to save in a formal account, identification of all factors is not in the scope of this study. Second, what is the exact role of pressure inside the household that does not allow earnings retention? These important questions we leave to future work.

6.A Appendix: Additional tables

Table A.6.1: Estimates for reinvestment and saving/saving practices relationship by using full sample

VARIABLES	(1) reinvest	(2) reinvest	(3) reinvest
Save formal	0.09***	0.09***	0.09***
	(0.02)	(0.02)	(0.02)
Save informal	0.06***		
	(0.01)		
Save informal individually		0.07***	0.07***
		(0.01)	(0.01)
Save informal with others		0.01	
		(0.02)	
Save with household members			-0.01
			(0.02)
Save with people outside household			0.04
			(0.03)
Borrowed	0.04**	0.04**	0.04**
	(0.02)	(0.02)	(0.02)
Education	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
Female	-0.03**	-0.03**	-0.03**
	(0.01)	(0.01)	(0.01)
Single	0.04**	0.04**	0.04**
	(0.02)	(0.02)	(0.02)
No training	-0.03***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)
Income	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)
Observations	5,803	5,803	5,803
Sample	All	All	All
Hypothesis:	p-values	p-values	p-values
H_o: Save formal - Save informal=0	0.072	-	-
H_o: Save formal - Save informal individually=0	-	0.182	0.176
H_o: Save formal - Save informal with others=0	-	0.001	-
H_o: Save formal - Save with household members=0	-	-	0.000
H_o: Save formal - Save with people outside household=0	-	-	0.066

Notes: Reinvestment is the dependent variable in the estimations. We report estimates marginal effects at mean values for all estimations and robust standard errors are in parentheses. We additionally control for sector and region dummies in the estimations. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6.2: Heterogeneity in the impact of saving in the household on reinvestment

	(1)	(2)	(3)	(4)
Dependendent variable:	reinvest	save with household members	reinvest	save with household members
Save with household embers	-0.81**		-0.86**	
	(0.37)		(0.41)	
Bank branch within one hour walking distance		-0.39***		
		(0.12)		
Min. distance to ATM, bank branch, or MFI				0.10***
				(0.04)
Age		-0.12***		-0.11***
		(0.03)		(0.04)
Age^2		0.00***		0.00***
		(0.00)		(0.00)
Borrowed	0.07	-0.98***	0.05	-0.97***
	(0.16)	(0.12)	(0.17)	(0.13)
Education	-0.07	-0.33***	-0.07	-0.34***
	(0.06)	(0.07)	(0.07)	(0.07)
Female	-0.24**	-0.27**	-0.31***	-0.28**
	(0.12)	(0.12)	(0.12)	(0.13)
Single	0.25	-0.47**	0.25	-0.44*
	(0.18)	(0.22)	(0.20)	(0.24)
Notraining	-0.32***	0.05	-0.36***	0.04
	(0.12)	(0.12)	(0.14)	(0.12)
Income	0.08	-0.28***	0.06	-0.27***
	(0.06)	(0.05)	(0.06)	(0.05)
Constant	0.05	8.51***	0.56	8.08***
	(1.07)	(0.97)	(1.23)	(1.08)
Observations	877	877	797	797

Notes: We report bivariate probit estimates. We report robust standard errors for columns 1 and 3 and clustered robust standard errors at ward level in columns 2-4 in parentheses. We use the sample for Formal Savers and Household Savers and formal savers as the base category. We additionally control for region dummies in the estimations. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6.3: Bivariate Probit Estimations

	(1)	(2)	(3)	(4)
Dependendent variable:	reinvest	save with household members	reinvest	save with household members
Save with household embers	-0.81**		-0.86**	
	(0.37)		(0.41)	
Bank branch within one hour walking distance		-0.39***		
		(0.12)		
Min. distance to ATM, bank branch, or MFI				0.10***
				(0.04)
Age		-0.12***		-0.11***
		(0.03)		(0.04)
Age^2		0.00***		0.00***
		(0.00)		(0.00)
Borrowed	0.07	-0.98***	0.05	-0.97***
	(0.16)	(0.12)	(0.17)	(0.13)
Education	-0.07	-0.33***	-0.07	-0.34***
	(0.06)	(0.07)	(0.07)	(0.07)
Female	-0.24**	-0.27**	-0.31***	-0.28**
	(0.12)	(0.12)	(0.12)	(0.13)
Single	0.25	-0.47**	0.25	-0.44*
	(0.18)	(0.22)	(0.20)	(0.24)
Notraining	-0.32***	0.05	-0.36***	0.04
	(0.12)	(0.12)	(0.14)	(0.12)
Income	0.08	-0.28***	0.06	-0.27***
	(0.06)	(0.05)	(0.06)	(0.05)
Constant	0.05	8.51***	0.56	8.08***
	(1.07)	(0.97)	(1.23)	(1.08)
Observations	877	877	797	797

Notes: We report bivariate probit estimates. We report robust standard errors for columns 1 and 3 and clustered robust standard errors at ward level in columns 2-4 in parentheses. We use the sample for Formal Savers and Household Savers and formal savers as the base category. We additionally control for region dummies in the estimations. *** p<0.01, ** p<0.05, * p<0.1.

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